University of Southern Queensland

Faculty of Health, Engineering and Sciences

To define and model meteorological drought in the Northern Agricultural Region of Western Australia

A dissertation submitted by

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Abstract

Drought is one of the least understood natural hazards on account of the complex dynamics between climatology and meteorology that drive it. Monitoring and quantifying drought is critical to many aspects of life particularly given the predicted changes to rainfall, temperature and variability associated with climate change. For dryland farming in Australia accurate forecasting will determine the preparedness for this change, especially in a region which is seemingly caught between two climate drivers as they alternately track up and down the west coast.

The motivation behind this research is to firstly contribute to the coverage of historical rainfall data by digitising farm-based records before conducting localised predictions for a region misrepresented by current methods. This is achieved through the application of meteorological drought indices to 38 stations across the North Midlands, an area within the Northern Agricultural region of Western Australia. This research provides valuable classification of the meteorological drought characteristics with respect to the study area's wheat growing period for use by both farmers and drought response agencies.

Windmere station has been found to be reliable in comparison to the nearest Bureau of Meteorology station and when coupled with anecdotal evidence is providing a unique insight. It has emerged that although a generalised May to October growing period currently captures drought in the study area, selecting a localised growing period that more frequently represents the North Midland's shorter season is important to accurately determine agricultural drought from meteorological indices. Spatial analysis in this study indicates that the North Midlands region differs greatly in frequency and onset of drought when compared with the greater South West Agricultural Region. However, there is evidently a need for greater research in this area to develop applicable combined indices capable of incorporating crop water availability accurately, particularly with the increased risk of temperature induced drought.

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Jessica Mendonca

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Thank you,

Jessica Mendonca

Table of Contents

List of Figures

List of Tables

1. INTRODUCTION

According to research by the Australian Greenhouse Office, 'about 50% of the rainfall decrease in southwestern Australia since the late 1960s is likely due to increased greenhouse gases' (Hennessy, K. et al. 2008, p. 3; Sudmeyer et al. 2016). The Australian Bureau of Agriculture (2017) found climate change to have negatively impacted dryland cropping productivity by 10-20% in the 15 years to 2015 across vast areas of Western Australia's Northern Agricultural region. Despite the same report suggesting farmers had adapted to climate change, anecdotal evidence reveals this is likely due to maximised performance in the better years, leaving many exposed to poor seasons. Predicting the occurrence of climatic extremes, such as drought, to guide adaptions in farming practice and land-use will inevitably be crucial to the survival of the industry.

Given the reliance on winter rainfalls, the steady increase in the presence of dry synoptic conditions in early winter and associated shift in climatic zones across southwestern Australia is placing significant pressure on cropping in marginal tracts (Indian Ocean Climate Initiative 2012; Guthrie et al. 2015). Dr Andrew Fletcher from the CSIRO suggested this year that without continuous improvement in agronomy and plant selection there will be a decrease in the Western Australian wheat yield as the climatic zone shifts at an increasing rate towards the coast. Compounded by predictions for slightly heavier rainfall events in the 95th percentile separated by longer dry spells, the result is more extreme impacts on natural ecosystems, society and infrastructure (Indian Ocean Climate Initiative 2012). Evidently, long term impacts on a region that supplies the nation's economy with approximately one quarter of its crop will have widespread consequences (Heard 2019). Climate change is inevitably affecting natural environment and in turn the human habitation supported by it (AGRIC 2018).

Recent widespread fires across many states of Australia highlighted the potential catastrophic nature of drought conditions. Unfortunately, the inability to reliably quantify such relationships at present combined with the uncertainty of how changes to population demographics, economic drivers and technology advancements will contribute to such consequences leaves room for conjecture (*The Physical Science Basis* 2007). Despite the anthropogenic influence on drought occasionally being a contentious issue most people can agree that drought is a hazardous climatic phenomenon that results in insufficient water availability with numerous consequences . The significance of drought differs according to the prevalence of its impact on community needs hence it is typically classified into four types:

1. Meteorological drought: a prolonged period where atmospheric conditions have yielded low rainfall.
2. Hydrological drought: reduced surface or subsurface flows due to a sustained period of dryness. Low streamflow, groundwater, and water storage levels may persist beyond the end of an associated meteorological drought.
3. Agricultural drought: temporary low soil moisture levels during a critical growing period – not necessarily associated with meteorological drought – that typically impacts crops, pasture, and stock.

4. Socio-economic drought: reduced productivity of economic goods and diminished community welfare.

(Hennessy, K. et al. 2008, p. 3)

Due to the subjective nature of drought it is often defined in relative terms as the result of lower than normal levels of rainfall. Although not precise, the Australian climate can thus be viewed as a stochastic system, based on the random probability of historical experiences reoccurring (Hertzler et al. 2013). In the past Australian drought policy has adopted a 1 in every 20-25 years drought concept in order to define the critical threshold for drought assistance (Hennessy, K et al. 2008). This concept attempts to characterise rare events as those in the 5^{th} percentile of the driest years on record; however with exceptionally low rainfall 'unprecedented in its geographic extent, length and severity' new measures are being adopted to manage drought (Hennessy, K et al. 2008, p. 21).

This dissertation will work to collate rainfall records not previously digitised, thereby enhancing drought modelling and providing invaluable information to support on farm decisions. Despite recent advancements in forecasting models using the correlation between real time atmospheric conditions and rainfall, working to remove the reliance on assumptions, predicting drought within a useful timeframe largely continues to be based on historical time series analysis (Ramsundram et al. 2016). It is a complex task considering the dynamics of climatic drivers that influence Australia to have 'one of the most variable climates in the world' (Hennessy, K. et al. 2008, p. 3).

1.1 Aims

Given the complex task of forecasting drought the aim of this work is to highlight the importance of developing regionally specific models. This will involve the evaluation of three meteorological drought indices across varying time scales to determine their relevance in declaring agricultural drought. The purpose, rather than solely providing a threshold for drought assistance, is to improve the guidance to government agencies responsible for research and development and in turn provide farmers with reliable early warning systems and drought tolerant solutions. Given the numerous influences on wheat yield, this work will instead capture anecdotal evidence to determine the ability of the drought models with specific reference to the growing period of the study area. By this method drought management strategies that work to alleviate the trend of shifting climatic zones will be drawn.

1.2 Objectives

As outlined in the Appendix A1 Project Specification:

1. Define the characteristics of meteorological drought

2. Define indices relevant to meteorological drought in WA

3. Literature review with particular reference to the consequence of shifting climatic zones in Northern Agricultural Region of WA
4. Conduct spatial and temporal analysis of meteorological drought in Northern Agricultural Region WA specifically for the winter growing period using rainfall data from both BOM and other sources not previously digitised
5. Quantify likelihood of future meteorological drought for Northern Agricultural Region of WA based on 4.

If time and resources permit:

6. Conduct spatial and temporal analysis of meteorological drought in Northern Agricultural Region WA using rainfall and temperature
7. Develop a drought management strategy applicable to farmers in the Northern Agricultural Region WA

2. LITERATURE REVIEW

2.1 Definitions

2.1.1 Drought

Drought, as opposed to desertification, is a relatively short-term manifestation of climatic variations (Sen 2008). Despite droughts occurring in almost all climate types it is difficult to define due to its subjective nature. Meteorological drought, for instance, is said to develop as a result of successive years of below average rainfall leading to an 'acute water shortage' (ABS 1988, p. para. 2). This, however, fails to consider the contribution that evapotranspiration has in exacerbating drought conditions. To a farmer, this would not relate to the availability of subsoil moisture nor is it likely to relate to what is perceived as normal for the growing period. Hence there are several definitions for specific types of drought as outlined earlier.

Accordingly, the footprint of drought is also considered to determine the relevant definition. Although the impacts of drought may be considered reversible in some respects, it has the potential to devastate the environment, the economy, and the livelihoods of people (Sen 2008). Persistent droughts have impacted Australia, for instance, in the following ways:

- Failure of crops and pastures due to low-soil moisture and heat stress threatening income streams for grain growers and increased prices for the consumer.
- Decline in water quality of dams and watercourses, increasing the potential for toxic algal blooms, prior to drying up. Reducing hydropower generation and industry.
- Stock death due to starvation or thirst.
- Increased reliance by primary producers on supplement feeding and trucking water at additional cost to the business.
- Decline in profitability of businesses in rural communities as hardship drives farmers out of business.
- Severe loss of vegetation, promoting erosion.
- Increased risk of severe bushfires and dust storms.
- Loss of soil and vegetation.

(DoA&F 2014)

Unlike other hazards, the slow development of drought lends itself to monitoring (Svoboda & Fuchs 2016). In an attempt to characterise drought more definitively, rainfall statistics are used to relate conditions to long term historical records (Wilhite & Glantz 1985). Drought indices assess rainfall statistics by assimilation of various water balance indicators and periods to identify occurrences of drought and rate the severity in terms of areal extent, intensity, duration onset and cessation.

2.1.2 Dryland Farming

Dryland farming is an efficient agricultural system focused on water conservation through soil and water management (Turner 2004). Despite some agencies confining dryland farming to rain-fed agricultural production in semiarid areas, which receive between 250-500mm of rainfall, dryland farming practices are adopted by majority of Western Australia's gain-belt to overcome unevenly distributed rainfall and soil fertility (Anderson et al. 2016). In this sense, Western Australia's dryland farming is synonymous with rain-fed farming.

With 40% of Western Australia's wheat produced in areas with an average annual rainfall of less than 325mm and yields typically low by global standards, large scale mechanised enterprises are used to compensate (Hertzler et al. 2013; GRDC 2015). Dryland farming is often utilised in an environment where potential evaporation periodically exceeds precipitation, making is well suited to Western Australia given its heavy reliance on seasonal rainfall for grain production (Evans et al. 2019). With much of the world population dependent on dryland farming for cereal production, sustainability through agronomic and technological advances is crucial.

2.1.3 Growing Period

The predominant crop grown in Western Australia's south-west Mediterranean-type climate is wheat; however, barley, lupins, canola, and several other cereals are often grown alongside livestock in mixed farming systems. Like other crops that thrive in the short season of dryland farming, wheat is a winter active plant generally sown in the break of autumn rain, before setting seed in spring towards the onset of higher temperatures and decreased rainfalls (Turner 2004). In order of importance, wheat yields are influenced by the timing within the growing period and intensity of 'rainfall, solar radiation and temperature' (Hertzler et al. 2013, p. 62). Plant selection and breeding to improve the likes of drought tolerance has seen a rapid rise in productivity since the 1980's.

Despite some guidance encouraging farmers to capture early season falls with longer season varieties, the autumn break of 'at least 25 mm of rainfall over three days' typically falls in late May for the North Midlands (CSIRO & BoM 2019, p. 3). Wheat may however germinate on as little as 5mm in furrow cultivation. The window of opportunity for sowing, therefore, varies year to year depending on rainfall distribution, variety, soil type and farm management. The Department of Agriculture regards May and August which coincides with germination and flowering, respectively, to be when wheat is most sensitive to reduced rainfall (GRDC 2015). Given the determinate nature of wheat the plant reaches maturity around mid-September, as days lengthen, and temperatures begin to spike (see Evaporation (E) in Figure 1); regardless of the length of season.

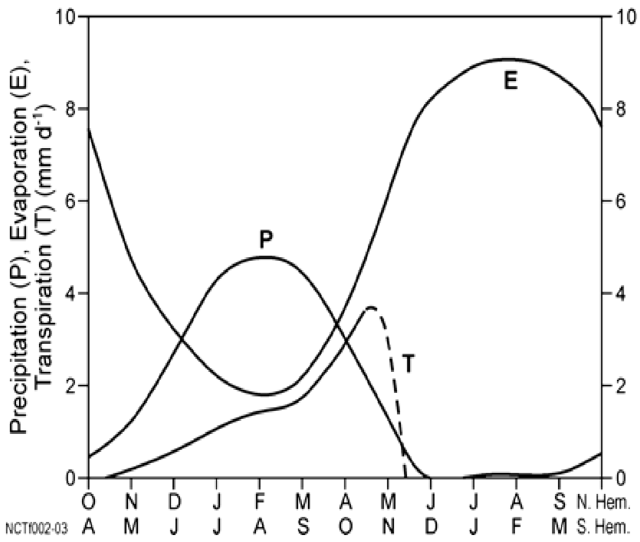

Figure 1: Typical Precipitation (P), Pan Evaporation (E), and Plant Transpiration (T) in a Mediterranean climate (Turner 2004)

The Western Australian wheatbelt growing period, in which local weather conditions are adequate for regular plant growth, is broadly regarded as May to October. However, considering the warmer, 'short season environment of the northern and eastern wheatbelt' October should be omitted when discussing the Northern Agricultural region (GRDC 2015, p. 12). Overlooking climate variability in defining the growing period has resulted in misleading statistics that fail to 'detect emerging drought conditions' in the past (Wilhite & Glantz 1985). The growing period for the North Midlands region in this research is therefore taken as the period from May to September, inclusive.

2.1.4 Precipitation

According to the Bureau of Meteorology (2007), precipitation is measured as the total liquid depth of water substance that falls over a 24hr period, including (but not limited to) rain, dew, frost, and hail. Considering the cases of frozen water precipitation are limited in the North Midlands, and even less captured by the gauge, rainfall will be used from this point to refer to the recorded precipitation.

2.1.5 Rain Gauge Error

The Bureau of Meteorology (BoM), formed in 1908, is Australia's national weather service and, among a multitude of other operations, provides access to rainfall observations throughout regional Western Australia. For many years regional landowners have volunteered contributions to the daily rainfall observations under guidance of the bureau, hence developing a standard practice for rainfall observation via the manual rain gauge (BoM 2007). The standard gauge is cylindrical with a 203mm diameter orifice funnelled into a graduated cylinder capable of measuring 25mm of liquid water depth. Overflow is captured by an outer vessel for larger rain events. It is recommended that the opening of the gauge is mounted 0.3m above the ground at a distance of at least twice the height of any nearby obstructions.

The gauge is read at 9am local time each day to account for 24hrs of rainfall, however on occasion when the observations are made over a longer period an accumulated total is recorded. In January 1974 BoM converted to the metric system of measure; however the custom of reading rainfall to the nearest 1 point, or 1/100th of an inch continues in many places today despite the standard cylinder often only displaying half millimetre graduations (BoM 2007). This is true at Windmere station. The accurate conversion is 1mm to 3.94 points, however in this case 4 points are recorded per each millimetre observed. In areas, such as this, that observe relatively small rainfalls the consequence of the error is greater. Further potential for error is introduced with observation requiring the gauge to be held level and the reading to be taken as the depth at the bottom of the liquid surface, rather than the top of the meniscus where it adheres to the side of the gauge.

Beyond human error, it is a well-researched fact that the wind distorts rainfall measurements by carrying smaller droplets to the 'lee side of the gauge orifice'. In fact, aerodynamic and wetting losses, as rain splashes out of or adheres to parts of the gauge, are regarded as the main contributors to rain gauge error (Sevruk 1987, p. 478). Hail, frost, and snow, although not overly common in the North Midlands, are also poorly captured despite contributing to soil moisture and crop yield. Limitations on fixed rain gauge measurements also extent to their inability to account for variable rainfall distribution.

2.1.6 Rainfall Variability

As opposed to rainfall reliability, rainfall variability is defined as the consistency of rainfall not only in time but also space. The heterogeneous behaviour of rainfall can also be 'expressed as the ratio between the standard deviation and the average value' (Morales 1977, p. 30). Both temporal and areal variability are influenced by climate drivers and atmospheric conditions as evident by the disparity of rainfall between seasons and regions. Additionally, areal variability is highly influenced by other environmental factors such as distance from the coast, impeding topography, and land surface feedback.

Vegetation cover, for instance, creates a localised micro-climate which controls humidity and temperature via transpiration. It influences cloud formation with the release of water vapour and varies the energy balances which drive climate by altering the surface albedo and levels of radiation absorbed. A dry spell in short-rooted crops reduces the advection of moisture into the atmosphere by transpiration, resulting in a raise in air temperature surrounding the plant canopy as radiation is absorbed (Belusic 2015). Logically, research finds rainfall variability to increase in more arid, typically sporadically vegetated, environments (Morales 1977; Wheater et al. 2002).

Similarly, increased soil moisture has been found to enhance local rainfall under thermally unstable and relatively dry lower atmospheric conditions as it induces thermal convection (Pan et al. 1996). Despite the need for more research into Australian micro-climates, these influences on local rainfall potentially explain the phenomenon of rain clouds seemingly tracking over the same localities during successive rain events (see Figure 2). The accumulated result is a high degree of both areal and temporal variability in the North Midlands, with BoM recording an index for the region ranging from moderate (1.0) to extreme (> 2.0) beyond the growing period, whilst other parts of the southwest land division tend to experience both delayed onset and a lesser degree of rainfall variability (Figure 3).

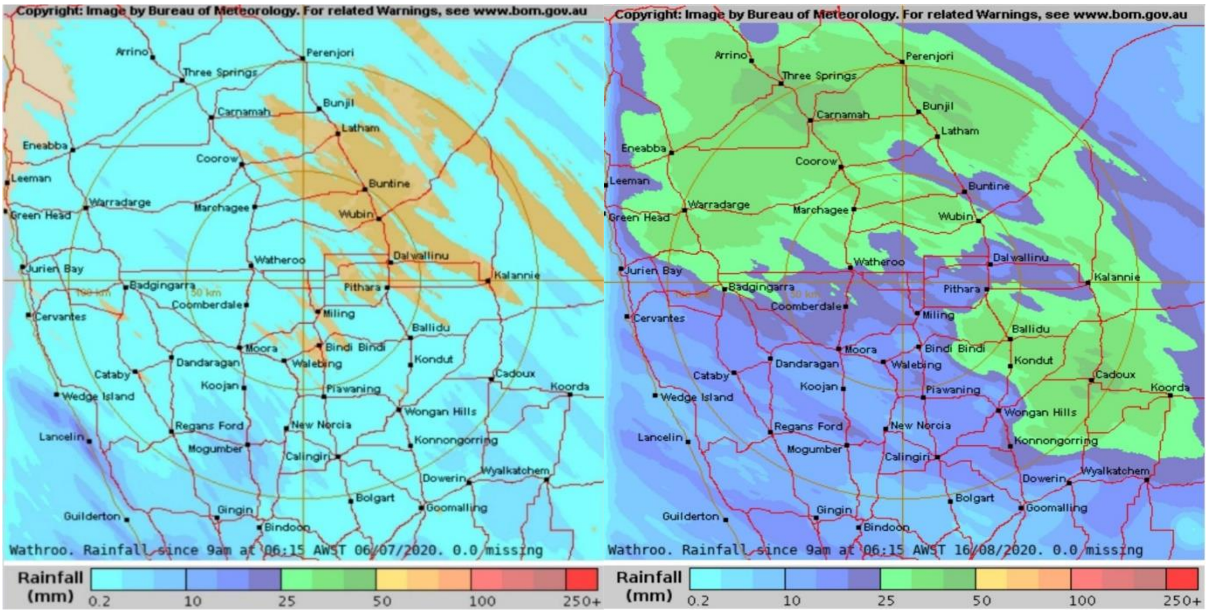

Figure 2: Spatial rainfall variability in the lower North Midlands captured by BoM's Rainfall since 9am radar product on 6th July & 9th August 2020 Note: the consistently lower rainfalls around Buntine and Dalwallinu townsites.

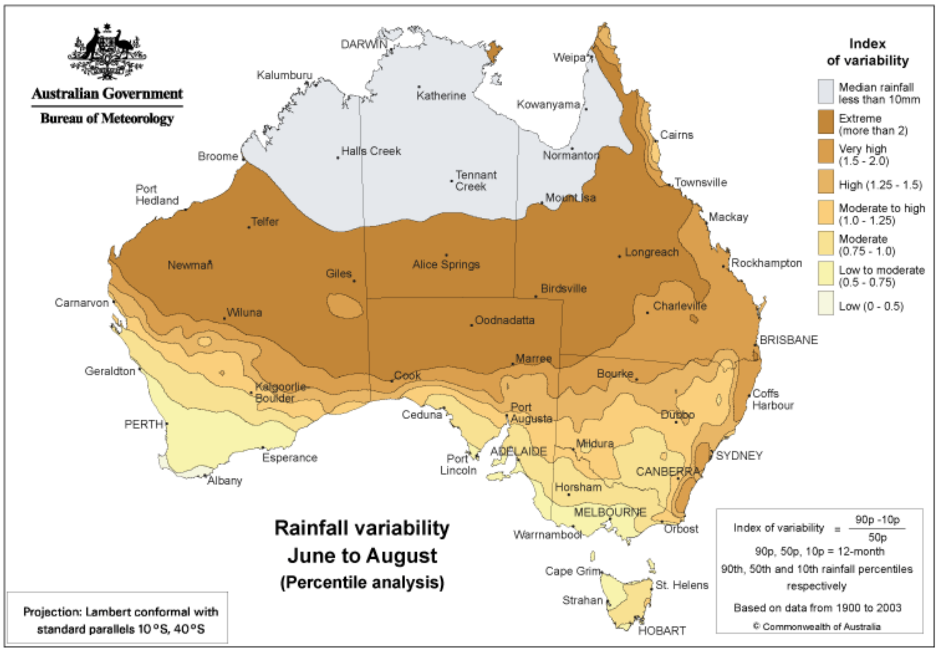

Figure 3: Winter Rainfall Variability courtesy of BoM (2019a)

2.2 Background

2.2.1 Prevalence of Drought in Western Australia

Although considered a defining characteristic of the Australian climate since the 1970s, drought is recognised as an abnormal event (Hennessy, K et al. 2008; Mpelasoka et al. 2008). At Windmere, in the North Midlands region of Western Australia, the current generation of farmers recount nine occasions in which crops went unplanted or failed due to drought conditions as outlined in Table 1. A heuristic rule used in this area suggests viable crop needs 125mm of growing period rainfall, with every inch above that equivalent to at least a bag (42.6kg) to the acre. With that in mind, 2007 is considered the most severe on account of its impact despite advances in farming practices over the past 40 years (Waite & Waite 2020).

With drought in the region being recorded on numerous occasions prior to this period, including between 1933-38 and 1947-50, speculation is that there is a near-decade drought cycle at play (ABS 1988). Although droughts remain unpredictable drought policy continues to evolve to support businesses. With 2019 recording very much below average rainfall for much of the country, federally funded drought assistance is being currently being distributed, including to the North Midlands, an area which was previously assessed in the same context as the eastern states despite relying on only one growing season per year (DoA&F 2014). Interestingly, although 2019 was a poor year for the North Midlands the situation is much more dire in the Southwest where the State Government is currently transporting water to more than a dozen towns to supplement depleted drinking water supplies (Daly et al. 2020).

Table 1: Agricultural droughts at Windmere (1977 – 2019) deduced from record and interview (*Climate Data Online* 2020; Waite & Waite 2020)

Deficient Year	Description
1976	Failure of autumn-winter rains, no break to season
1977	Early break, exceptionally early/dry finish
1979	Growing period rainfall of 128mm, June break, dry finish
1994	Dry start and finish, hottest May on record, growing period rainfall of 176.5mm
2002	No break to the season
2006	No break to the season
2007	No break to the season, worst year on record (112.5mm for growing period)
2017	No break to the season
2019	Late break, below average growing period rainfall (178.75mm), warm finish (hottest September on record)

2.2.2 South-west Climate Drivers

Climate refers to the normal course of weather or atmospheric conditions (BoM 2019b). With 80% of the annual rainfall recorded between the months of April and October the South-west climate is considered winter dominant with increased rainfall typically within proximity to the coast (Sudmeyer et al. 2016, p. p12). It is characterised by hot, dry summers with the winter frontal systems bringing moist, unstable winds. Current research reveals three climate drivers influence south-west rainfall more so than others, namely the Southern Annular Mode (SAM), Indian Ocean Dipole (IOD), and Southern Oscillation Index (SOI) (Indian Ocean Climate Initiative 2012; BoM 2019b; CSIRO & BoM 2019).

Most notably, the 'drivers influencing rainfall in the south-west differ from those of the rest of Australia' with studies finding the 'relationship between El Nino – Southern Oscillation (ENSO) and south-west rainfall' to be weak (Evans et al. 2019, p. 2). Despite being considered a secondary driver of the Australian Climate the SAM is highly influential in the south-west (Daly 2019). In winter, rain bearing fronts are drawn up across the south-west corner by a band of westerly winds from the Antarctic in what is regarded as a negative SAM phase (BoM 2019b). Alternatively, a positive phase in winter relates to higher pressures over southern Australia and a contraction of the westerly winds toward Antarctica which brings fewer fronts and drier conditions.

Between November and April, the influence of SAM on southern Australia is reduced by a southerly contraction of subtropical ridge, a belt of high pressure that encircles the globe (Sudmeyer et al. 2016; BoM 2019b). Under these conditions frontal activity from the south is suppressed, bringing about longer periods of dry and stable conditions however allowing moist tropical air to migrate further south to the mid-latitudes. On occasion, monsoonal activity and tropical cyclones developing in the far north sweep southward delivering 'moderate wind and rain' during this period (Sudmeyer et al. 2016, p. 13).

IOD relates to anomalous sea surface temperatures oscillating over a typical 4-5 year period in the Western Indian Ocean that contribute to the development of north-west cloudband activity (Telcik & Pattiaratchi 2014). Warmer than average temperatures associated with IOD encourage humid tropical air to migrate towards the poles and when faced with the high-pressure systems often present over Australia it is forced over cooler mid-latitude air mass (BoM 2019b). Under these conditions north-west cloudbands, which can extend back as far as Sumatra (see Figure 4), are promoted with greater frequency and have the potential to deliver soaking rains. Although north-west cloudbands can occur at any time of the year, they are responsible for much of the winter rainfalls across northern and central Australia.

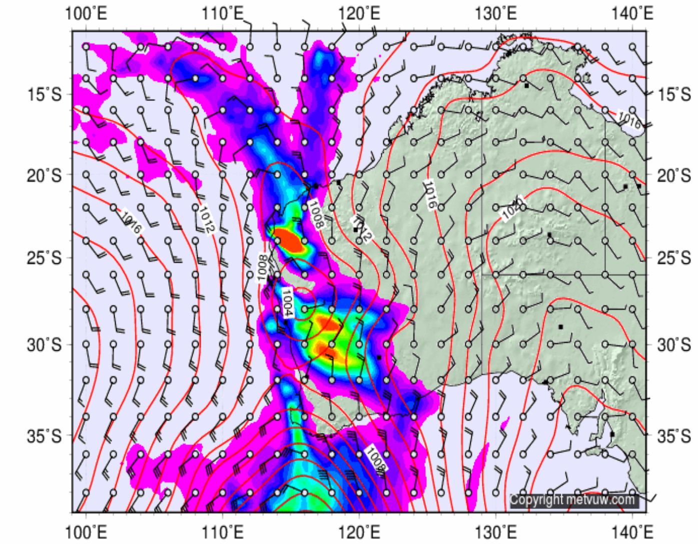

Figure 4: North-west cloudband interacting with a mid-level front 25 May 2020 courtesy of Metvuw

Evidently, differing climatic conditions are experienced across regions as the interaction between varying drivers develops. Given the 'strong spatial gradient from the south-west coast to the north-east inland' the north-eastern reaches of the South-west land division tend to experience less frequent and lower intensity rainfalls than its southern counterparts (Charles et al. 2010, p. iii). The Northern Agricultural Region for instance rely on the interaction between the north-west cloudband and mid-level systems to deliver soaking rains during the growing period, whilst the more frequent winter fronts typically only bring scattered showers, short periods of intense rain, as they sweep up from the south. Late season tropical cyclones and autumn storms, although erratic, can also contribute to subsoil moisture to support crop yield (GRDC 2015).

Over the past century, however most alarmingly in the past two decades, the warming and drying of the south-west has seen a migration of climatic zones approximately 70km towards the coast, see Figure 5 (Guthrie et al. 2015; Foster & Sudmeyer 2019; Heard 2019). Historically higher rainfall areas, once restrained by fungal disease and machinery movement in marshy paddocks are increasingly becoming viable for grain production, whilst the increase in temperature is also reducing the incidents of frost (Hertzler et al. 2013). However, research by Ludwig et al in 2009 suggests that the overall influence on the state's wheat yield is likely to be negative with the decline in early winter rainfall making it difficult to develop pasture for livestock, often a vital cropping rotation, and the incidence of dryland salinity set to spread with reduced natural drainage (Hertzler et al. 2013). Lower rainfall regions are altogether becoming less profitable and increasingly unreliable with diminished growing season rainfalls (Daly 2019).

Despite the drying trend between May to July for the South-west, the Indian Ocean Climate Initiative (2012) found increased July rainfall in central Western Australia to be consistent with the changing dynamic. Research by Evans, Guthrie and Foster (2019) indicated an increasing trend of cooling off the west coast since 1975 was likely hindering the mechanism of rainfall developing from the advection of water vapour in the Indian Ocean being swept across the south-west by subtropical storms or fronts. However, lying at the convergence of the tropical Hadley and lower mid-latitude cells (as in Figure 6) the Northern Agricultural region is more so reliant on the increasingly accessible north-west cloudbands (Sudmeyer et al. 2016, p. 13; Reid et al. 2019). This trend, nevertheless, is unlikely to negate the additional influence of historically increasing global air and ocean temperatures on Western Australia's climate; all of which make the task of forecasting drought increasingly challenging (CSIRO & BoM 2018).

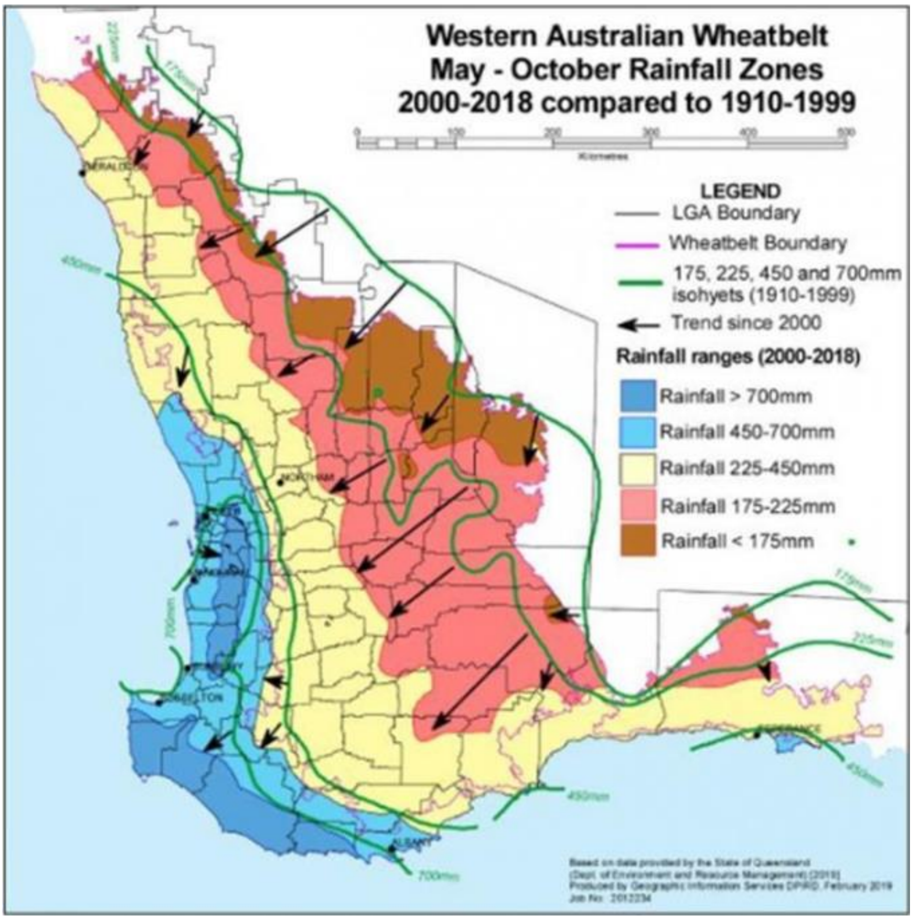

Figure 5: Migrating Climate Zones (Foster & Sudmeyer 2019)

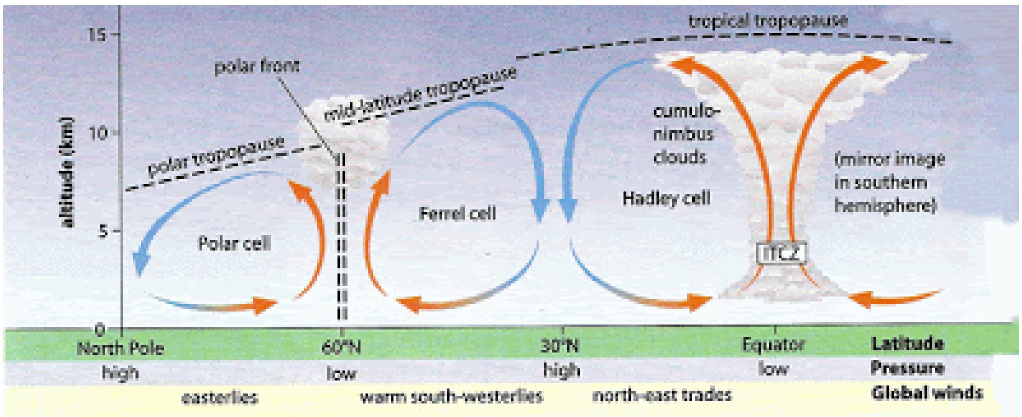

Figure 6: Atmospheric Circulation (Harriet 2008)

2.2.3 North Midlands Agricultural Region

The North Midlands is a farming district encompassed by the lower half of Western Australia's Northern agro-ecological zone; an area considered to be of similar rainfall and length of growing seasons (Hertzler et al. 2013). Under SA2 divisions the Australian Bureau of Statistics designates this area as 'Morowa' however for the purposes of this study it will be assumed to also include the coastal region of 'Irwin'. The study area, of more than 25,000 square kilometres, comprises the local government councils outlined in Table 2 (and later mapped in Figure 11).

This region is characterised by steadily undulating hills that break away to coastal plain. The western tracts of the North Midlands region are predominately very sandy soils supporting acacia scrub-heath. Whilst to the east heavier red loam, yellow sandplain, gravel, and clay lie widely cleared for cereal cultivation with remnant acacia-melaleuca thicket and eucalypt woodlands. Low natural fertility, production induced acidity and salinity are the major soil constraints for agriculture in the region (GRDC 2015).

Table 2: Demographics of the North Midlands region (Data by Regions 2018)

Council	Approx. Area (sq. km)	Population
Coorow	4,193	1004
Carnamah	2,384	541
Three Springs	2,657	591
Perenjori	8,313	596
Morawa	3,516	698
Mingenew	1,939	432
Irwin	2,374	3749

Despite typically relying on a single rain-fed winter crop, the North Midlands is one of Australia's most productive grain growing regions (see Figure 7) with 200 – 500kt produced on average each season (ABS 2018). According to the Natural Resource Management guidelines the Northern Agricultural region 'contributed almost $1.4 billion to the Australian economy in 2017-18' (CSIRO & BoM 2019, p. 1). However, with predictions of increased temperature and reduced rainfall, the region is increasingly under question as a profitable region for agriculture (AGRIC 2018).

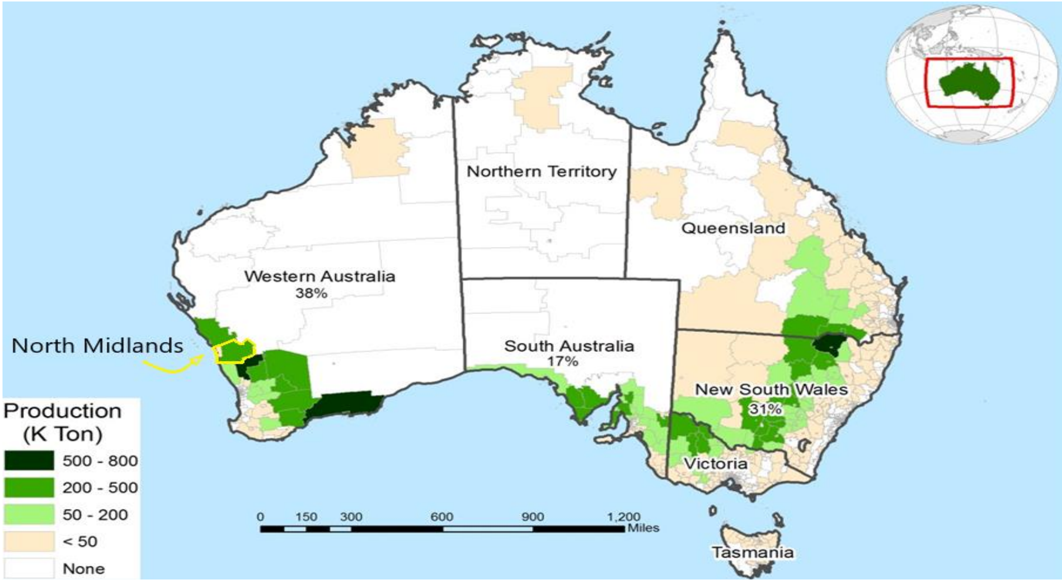

Figure 7: North Midlands Average Wheat Production adapted from USDA (2016)

2.2.4 Emergence as a Wheat Exporter

Development of the Swan Colony beyond the extent of the Swan River valley was initially difficult, however a strong economic period bolstered by the 1893 Kalgoorlie gold rush allowed Western Australia's founding government to pursue it's vision as an agricultural colony 'feeding the "bread-eating" nations of the world' (Hogstrom 1963; Hughes-d'Aeth et al. 2017, p. 15). In 1887, a parliamentary inquiry was tasked with mapping the direction of the agricultural industry resulting in several agricultural regions being declared.

With the completion of the Midland Railway in 1894 (Figure 8) and a range of land clearing programs, vast areas of agricultural settlement expanded into the North Midlands in the early 1900s (*Western Perspective of a Nation* 2003; Bowman-Bright 2018). In an area with very few rivers and permanent freshwater bodies, the viability improved with a better understanding of geology and widespread use of rain water tanks and dams (*Western Perspective of a Nation* 2003). Following traditional Noongar methods, soaks or wells were dug alongside granite outcrops where water naturally seeped (Hughes-d'Aeth et al. 2017).

Horse-drawn scrub rollers were used to uproot trees before the stripped trees and scrub were burnt in preparing for cultivation. This labour intensive work was encouraged by favourable economic conditions and an influx of return soldiers taking up the Group Settlement Scheme in the 1920s (*Western Perspective of a Nation* 2003). Despite the depression of the 1930s and ensuing poor profitability, land continued to be opened in marginal areas due to advancements in mechanical equipment and farming practice including the introduction of phosphate fertilisers.

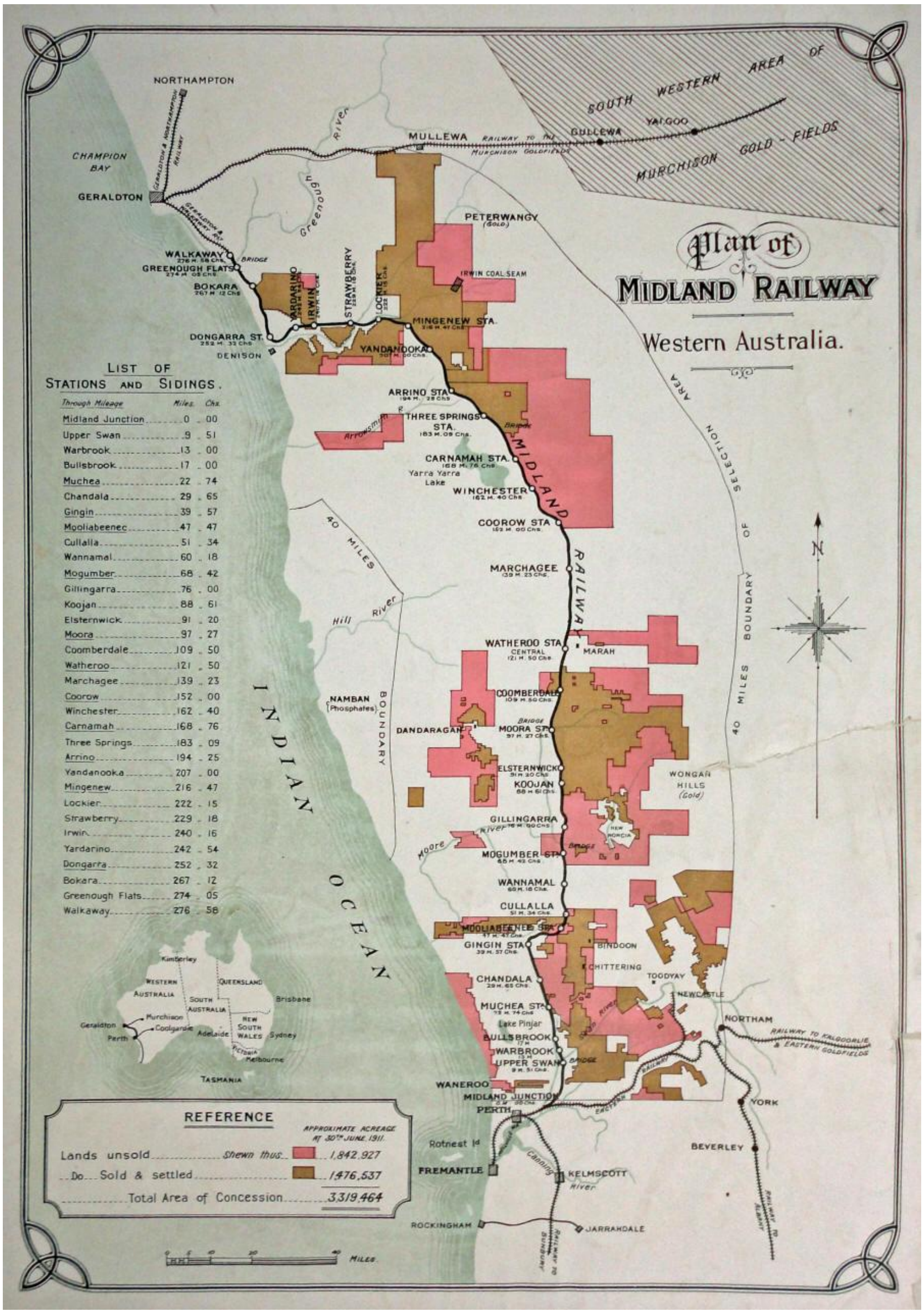

Figure 8: Midland Railway Land Grant 1912 (Bowman-Bright 2018)

In 1917, Surveyor-General F.S. Brockman was commissioned by the state government to delineate the extent of viable cropping in an effort to ensure sustainable development. The Brockman's Line (see Figure 9) named after the survey, followed similar efforts by George Goyder in 1865 who used vegetation after a sustained period of drought in South Australia to segregate areas 'where rainfall was reliable and where drought prevailed' (Leonard 2016, p. para2). Both lines are colloquially termed 10-inch lines, referring to the 250mm annual average rainfall isohyet.

No-till farming techniques, such as minimising degradation of soil structure and limiting the impact of disease and pests by removing summer weeds and volunteer wheat four weeks prior to seeding, continued the expansion of the viable region by working to retain soil moisture and lessening its demand (GRDC 2015). By 1980 almost 15 million hectares of land had been cleared for agriculture in Western Australia, most significantly for wheat production, before the unintended consequence of salinity due to a rising water table and an invasion of rabbits in search of food began to hinder the industry (*Western Perspective of a Nation* 2003). Today the Western Australian wheatbelt is bounded by the rabbit proof fence, which essentially follows Brockman's line to the north and east, and the 750mm annual average rainfall isohyet to the south and west. Beyond these boundaries wheat production is considered marginal due to intolerable rainfalls, too little to the east and too much to the west (Hughes-d'Aeth et al. 2017).

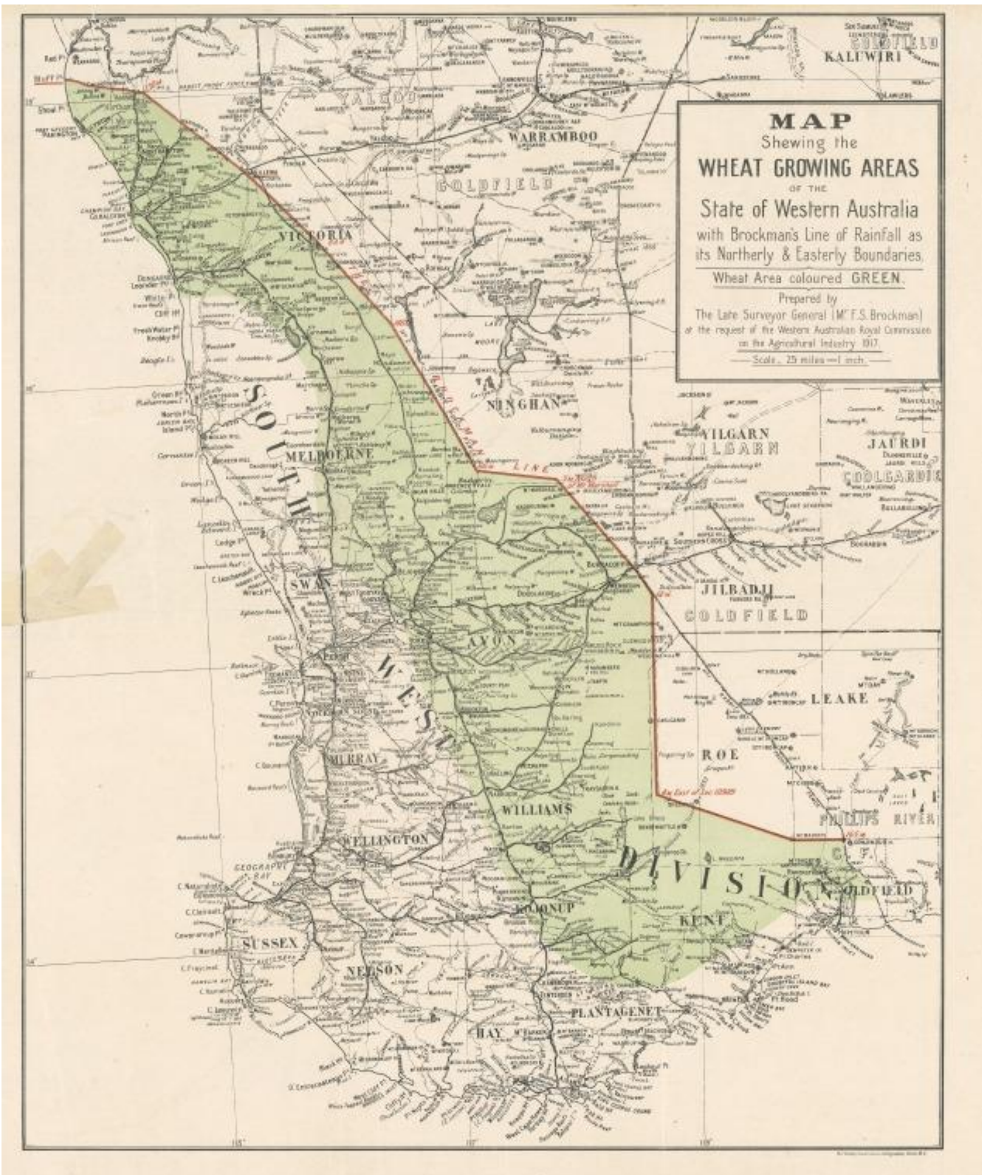

Figure 9: Map showing Brockman's Line (Brockman & Pether 1917)

2.2.5 Significance of Research

The real-time monitoring of Australia's surface climate variability, specifically the likelihood and severity of droughts are used to manage risk and make crucial decisions that impact both humans and the environment. There are significant discussions surrounding the robustness of the water resource management, infrastructure design such as roads, reservoirs and buildings and catchment planning; however, given the significance of agriculture in Western Australia its response to shifting climatic zones is of equal importance. Aligning the expectation and demand for water availability with long term supply is crucial to minimise the impact of future climatic extremes. Informed decisions made on the most complete, and localised, available data will translate to reduced risk, improved productivity, and economic viability. This is vital to ensure regional populations are retained as custodians for country in marginal areas.

While modelling and characterisation of drought has featured significantly in research, 'the temporal and spatial assessment in terms of mapping drought risk' continues to form a research gap (Dayal et al. 2018, p. 2). This is compounded by the limited provisions for seasonal forecasts in Australia's Southwest with the arbitrary 'rolling three-month periods' classically used to delineate growing period found by both researchers and grain growers to be unreliable (Evans et al. 2019, p. 2). Furthermore, despite the significance of increasing temperature on crop viability, with CSIRO finding a strong relationship between the 2008 wheat yield and 'the ratio between rainfall (P) during the growing season (April to October) and potential evaporation (E)', there is an inadequate record of both observations and research in this area (Leonard 2016).

While this study will attempt to characterise meteorological drought with specific respect to the Northern Agricultural region's May to September growing period and contribute to the coverage of parameters available to probabilistic forecasts – there will clearly be further attention required in this area. Expedient action is crucial given the increasing loss of local knowledge and records as regional populations dwindle.

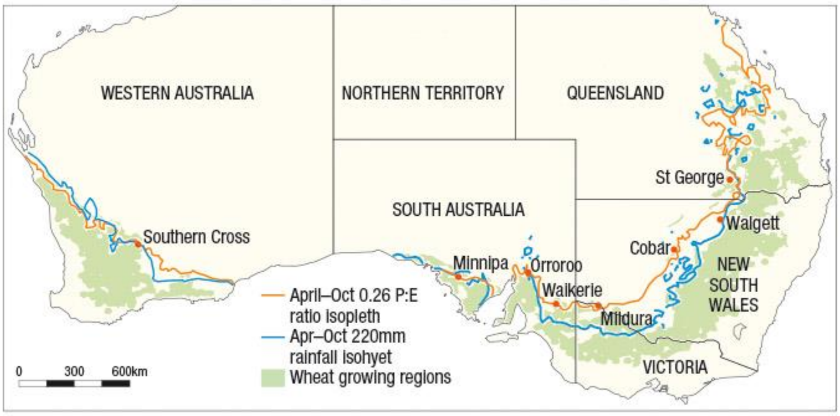

Figure 10: Comparison of wheat yield to Precipitation-Evaporation ratio (Leonard 2016)

3. METHODOLOGY

3.1 Interview

The first stage of this process is a case study of Windmere Station to direct data collection and analysis. An interview provides first-hand accounts of drought experience, rainfall records, and observed weather patterns. This information is used to distinguish between current consensus for the region and actual occurrence with regards to the growing period and climate variability. Importantly, it also provides an indication of the ability of the indices to capture drought. The full interview with the proprietors of Windmere is included in the Appendix A2.

3.2 Data Collection and Pre-processing

Data accessible at BoM Climate Data Online portal has undergone rigorous quality control and only those stations falling within the study site with a real record length (see equation 1 below) of 35 years or more have been adopted, leaving 37 BoM records (Table 3). Windmere station has been converted to a monthly millimetre record and added to the BoM records giving an average record length of 81 years. Notably, Morowa and Morowa Airport stations have been amalgamated and the location taken as the original Morowa coordinates. This is considered acceptable due to their proximity of approximately 1.7km.

$$real\,record\,length\ =\ [record\ length\ \times\ (1\ -\ fraction\,of\ missing\ data)]$$

(Equation 1)

Table 3: List of Selected Stations (Continued page 28)

Station Name	Shire Council	Period of Record	Estimated Completeness of Rainfall Record	Real Record Length (~years)	Coordinates	
					Latitude	Longitude
Windmere	Coorow	JAN 1977 - DEC 2019	100%	43	-29.8514	116.2863
Warradage	Coorow	APR 1980 - JUN 2019	98%	39	-30.0722	115.3136
Leeman	Coorow	FEB 1983 - JUN 2019	83%	36	-29.9486	114.9781
Coorow	Coorow	JAN 1912 - JUL 2019	94%	107	-29.8814	116.0229
Minaru	Coorow	JAN 1932 - JUN 2017	93%	85	-29.8497	116.2289
Koobabbie	Coorow	JAN 1911 - FEB 2019	100%	107	-29.9414	116.2003
Hakea	Coorow	AUG 1908 - JUN 2019	97%	110	-30.0989	116.2339
Ytiniche	Coorow	JAN 1913 - DEC 2018	100%	105	-30.0706	116.2092
Latham	Perenjori	JAN 1934 - JUL 2019	95%	85	-29.7586	116.4444
Perenjori	Perenjori	JAN 1918 - JUL 2019	90%	101	-29.4417	116.2875

Perangery	Perenjori	AUG 1910 - JUN 2016	94%	105	-29.3692	116.4061
Wanarra	Perenjori	JUN 1973 - MAY 2019	96%	46	-29.5147	116.8011
Oaklands	Perenjori	MAY 1967 - APR 2016	73%	49	-29.4667	116.1325
Five Gums	Perenjori	JAN 1945 - DEC 2018	95%	73	-29.4847	116.0703
Eneabba	Carnamah	MAY 1964 - MAR 2017	94%	52	-29.8183	115.2722
Twin Hills	Carnamah	MAY 1972 - SEP 2014	81%	42	-29.6708	115.3636
Carnamah	Carnamah	JUN 1887 - JUL 2019	84%	131	-29.6886	115.8872
Highfields	Carnamah	NOV 1956 - JUL 2019	96%	62	-29.6006	115.9392
Green Grove	Irwin	APR 1951 - JUN 2019	96%	68	-29.5486	115.0689
Irwin House	Irwin	JUN 1982 - JUN 2019	99%	37	-29.2236	115.1075
Dongara	Irwin	JAN 1884 - JUL 2019	81%	135	-29.2528	114.9306
Mindarra	Irwin	APR 1972 - NOV 2014	98%	42	-29.0636	115.1753
Three Springs	Three Springs	JAN 1907 - JUL 2019	97%	107	-29.5339	115.7628
Fairfield	Three Springs	NOV 1919 - SEP 2017	84%	97	-29.4714	115.8528
Mingenew	Mingenew	JAN 1896 - JUL 2019	88%	123	-29.1906	115.4414
Yandanooka	Mingenew	MAR 1903 - JUL 2019	93%	115	-29.2872	115.6331
Arena	Mingenew	JUL 1980 - JUL 2019	99%	39	-29.3586	115.4503
Yarragadee	Mingenew	JAN 1906 - MAY 2014	93%	107	-29.0767	115.4092
Manarra	Mingenew	SEP 1906 - JUL 2019	86%	112	-29.0711	115.6261
South Holmwood	Mingenew	JAN 1921 - JUL 2019	99%	98	-29.0364	115.5536
Strawberry North	Mingenew	SEP 1900 - DEC 2014	94%	113	-29.1514	115.2428
Morawa	Morawa	MAY 1911 - JUL 2019	96%	96	-29.2103	116.0089
Canna	Morawa	OCT 1915 - JUL 2019	96%	103	-28.8975	115.8627
Pindawa	Morawa	JAN 1958 - JUN 2019	99%	61	-28.8956	115.8106
Yongarloo	Morawa	JAN 1946 - AUG 2018	96%	72	-29.1858	115.7406
Mallee Vale	Morawa	JAN 1935 - JUN 2019	90%	84	-29.2419	115.7794
Nindethana Farm	Morawa	OCT 1977 - MAY 2019	100%	41	-28.8114	115.9675
Mellenbye	Morawa	SEP 1903 - JUL 2013	81%	109	-28.8883	116.1947

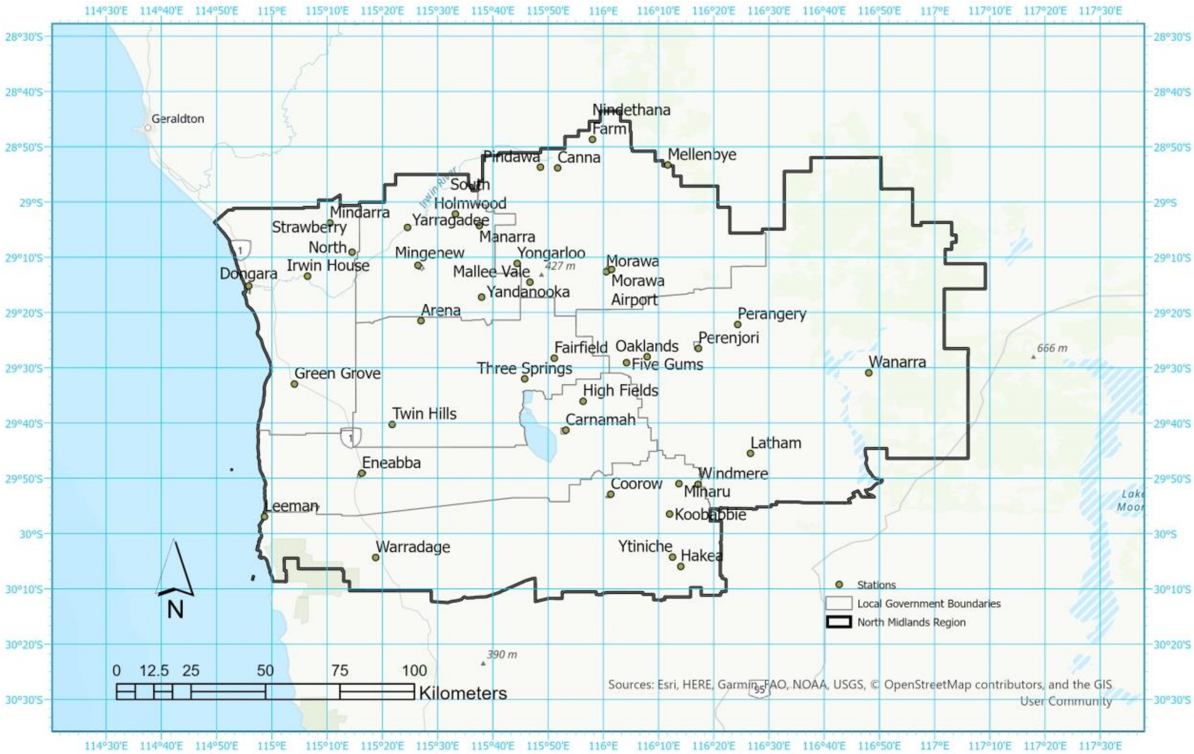

Figure 11: Selected stations within the North Midlands Region

3.3 Data Quality

Despite having confidence in the data drawn from personal contributions to the record, it would be erroneous to assume the quality of the entire data set. For instance, on the rare occasion there was no one present to record rainfall over several days the daily record would be inconsistent. Irrespective of the lack of information relating to accumulated observations, it is not likely to impact the reliability of this study due to the use of monthly accumulations for all index estimations.

Anecdotal evidence suggests if there were to be any periods of lesser reliability it would be during the first four years of the record given this was during the establishment of the farm. Given this period coincided with a number of dry years it is difficult to rule out variability as the source of disparity (see Figure 12) between Windmere 116.28°E, 29.85°S and the closest BoM station, Minaru 116.23°E, 29.85°S (5.5km away). Taking the record on face value, Windmere station is therefore estimated to be 100% complete between the period of January 1977 and December 2019 and no filling or adjustments will be made.

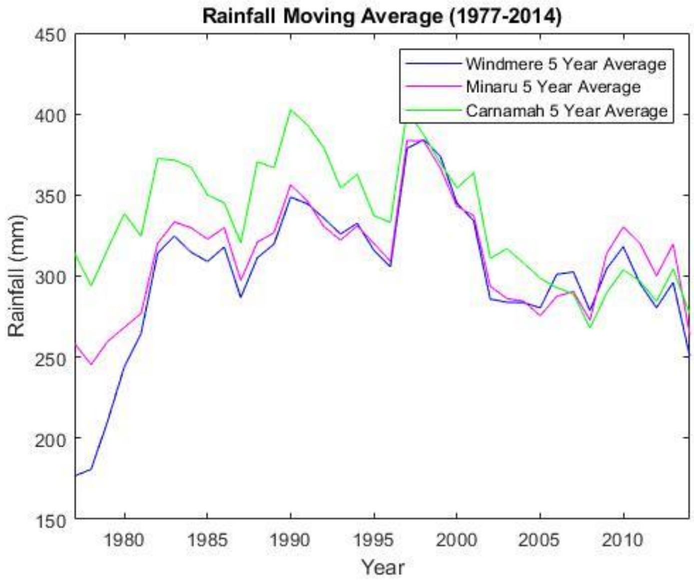

Figure 12: 5 Year Moving Average of Rainfalls recorded at Windmere, Minaru and Carnamah

3.4 Data Validation

3.4.1 Mann-Kendall Trend Test (Mann 1945, Kendall 1975, Gilbert 1987)

The Mann-Kendall test (M-K test) is a non-parametric monotonic analysis of trend; that is, it indicates whether there is an upward or downward trend by means of ranking the series of data. Originally developed to determine relationships between economic interest rates at different locations over time, the M-K test has become popular to analyse trends in environmental studies such as floods and droughts (Helsel & Frans 2006). Given that rainfall data is rarely symmetric in distribution the M-K test has 'a distinct advantage over linear regression, where normality of residuals is required' (Helsel & Frans 2006, p. 4066).

The non-parametric nature of the test ensures the length of record, missing data and non-consecutive periods of monitoring does not influence the analysis however serial correlation is not accounted for. This is typically relevant to rainfall analysis although the monotonic or single direction of the trend poses an issue given seasonal variation. This variation may be further exacerbated by the common practice of farmers taking holidays during the summer off season and the inherent error introduced during this period.

For this reason we will run a seasonally varied M-K test similar to that developed by Hirsch, Smith, and Slack in the 1980's (Hirsch & Slack 1984) to verify the relationship between both observed winter and growing period rainfall at Windmere 116.28°E, 29.85°S and the closest BoM station, Minaru 116.23°E, 29.85°S (approx. 5.5km away) to validate the reliability of the farm-based record. The same comparison will also be run against Carnamah 115.89°E, 29.69°S (approx. 44km away), being the closest BoM station with both rainfall and temperature records, in preparation for calculating Standardised Precipitation-Evapotranspiration Index (SPEI).

Given data series $x_i, x_j, \ldots, x_n$ the M-K test statistic is equated as,

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i)$$

(Equation 2 courtesy of Hussain et al. (2015))

Where, $sgn(x_j - x_i)$ is a comparison of the sign of each neighbouring data pair.

$$sgn(x_j - x_i) = \begin{cases} +1 \text{ if } (x_j - x_i) > 0 \\ 0 \text{ if } (x_j - x_i) = 0 \\ -1 \text{ if } (x_j - x_i) < 0 \end{cases}$$

The M-K test is then transformed to normal distribution with:

$$\text{mean,} \qquad E(S) = 0$$

(Equation 3)

$$\text{variance,} \qquad Var(S) = \frac{n(n-1)(2n+5) - \sum_{k-1}^{m} t_k(t_k - 1)(2t_k - 5)}{18}$$

(Equation 4)

$$\text{test statistic,} \qquad Z = \begin{cases} \frac{S-1}{\delta} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\delta} & \text{if } S < 0 \end{cases}$$

(Equation 5)

When Z is greater than zero an increasing trend is present, alternatively when Z is less than zero a decreasing trend is present (Gedefaw et al. 2018).

To test the relationship between the two stations the following hypothesis is set:
Null hypothesis (H_0) is that there is no monotonic trend in the series.
Alternate hypothesis (H_a) is that there is either an upward, downward, or non-null trend, where alpha (α) is the predetermined level of significance. In this instance α = 0.05 is adopted.

3.4.2 Sen Slope

The Sen Slope estimator test in this instance indicates the strength of the relationship determined by the M-K test. Trend analysis by this method is determined using a linear model; however, unlike linear regression Sen's Slope is not ‘affected by gross data errors and outliers’ (Kumar et al. 2017, p. 5). Sen’s Slope, Q_i is an estimation of the median slope of each pair of data values in the set. Individual slope values, T_i are calculated for each data point, where j and k are corresponding time values and $j > k$.

$$T_i = \frac{x_j - x_k}{j - k} \qquad for\ i = 1, 2, 3, \dots n$$

(Equation 6 courtesy of Hussain et al. (2015))

$$Q_i = \begin{cases} T_{\frac{n+1}{2}} & for\ n\ is\ odd \\ \frac{1}{2}\left(T_{\frac{n}{2}} + T_{\frac{n+2}{2}}\right) & for\ n\ is\ even \end{cases}$$

(Equation 7 courtesy of Hussain et al. (2015))

Similarly to the M-K test Tau coefficient, Sen’s slope represents the degree of concordance between the two columns of ranked data with a larger value of Q_i corresponds to a stronger relationship with increasing or upward trend if positive or decreasing or downward trend is negative.

3.5 Calculating Drought Indices

3.5.1 Deciles (Gibbs & Maher 1967)

Refined by the BoM Australia, the decile index is a statistical approach to rainfall analysis based on its relative position within the rank of the entire historical record for a specific region (Jones et al. 2009). To calculate deciles rainfall is accumulated into any month or multi-month period (e.g. monthly, quarterly, etc.) before being ranked in ascending order and divided into ten equally sized decile bands (see Figure 13). The first decile is simply the threshold which 90% of falls accumulated over the specified period exceeded (ABS 1988).The bands are then categorised ‘according to the degree of deviation from the average’ (as in table 4) (GRDC 2015, p. 9).

Table 4: Decile categories (AGRIC 2018)

Decile 1:	0 – 10%	Well Below Average
Decile 2-3:	10 – 30%	Below Average
Decile 4-7:	30 – 70%	Average
Decile 8-9:	70 – 90%	Above Average
Decile 10:	90 – 100%	Well Above Average

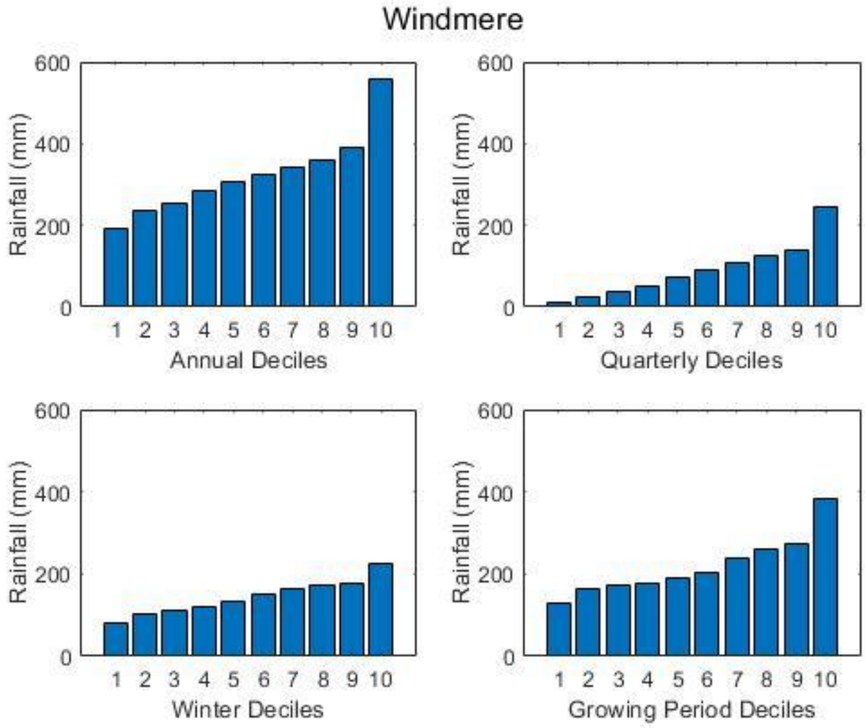

Figure 13: Windmere Decile Bands

The extreme ends of the distribution capture the driest and wettest years on record; however, the determination of drought varies according to the chosen methodology. Consensus does nevertheless regard rainfalls in the lowest 5% on record as 'severe rainfall deficiency' and those between 5-10% as 'serious rainfall deficiency' (White et al. 1999).

Beyond simplicity, deciles have the advantage of flexible timescales, ability to review wet years and being a parametric analysis does not assume any specific rainfall distribution. It does, however, fail to consider any other parameters influencing drought and there are several different approaches making it important to specify the methodology used (Svoboda & Fuchs 2016, p. 11). Measures of average rainfall can also be misleading with the frequency of low rainfall years potentially more than high rainfall years, dragging the average down irrespective of severity (GRDC 2015).

3.5.2 Standardised Precipitation Index (SPI) (McKee et al. 1993)

Derived from water balance techniques, SPI is a versatile index used to characterise drought according to historical rainfall accumulated over a range of time scales. Based solely on precipitation, short time scales of one or two months are applicable to dryland farming, for example, which is dependent on seasonal falls where small anomalies of soil moisture can influence production. Longer timescales, on the other hand, are typically used to model reservoir storage and groundwater flows.

$$SPI = (X - \overline{X})/\sigma$$

Where,

X = rainfall data series

$\overline{X}$ = long term mean of all data

σ = standard deviation of all data

(Equation 8 courtesy of World Meteorological Organisation (2012))

A three-monthly SPI, for example, is calculated by estimation of a three-monthly moving average in terms of a chosen probability distribution. This is most commonly achieved by allocating corresponding gamma cumulative distribution function values to each of the observed data points before being transformed to give the data set a mean equal to zero and a standard unity of one, therefore producing standard normalised SPI values. Positive SPI values indicate wetter than median rainfall whilst negative SPI values indicate drier than median rainfall as seen in Table 5 below. A drought in this sense is defined as any sustained period equal to or below -1.0 and continues until the SPI returns to a positive value (World Meteorological Organisation 2012).

Table 5: SPI categories (World Meteorological Organisation 2012, p. 4)

2.0+	extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	moderately wet
-.99 to .99	near normal
-1.0 to 1.49	moderately dry
-1.5 to -1.99	severely dry
-2 and less	extremely dry

SPI is the most used drought indicator due to its simplicity and ability for comparison of drought in distinctly different climatic areas (Jain et al. 2015). Given its sample size dependency, the WMO Users Guide recommends a minimum of 20-30 years of continuous rainfall data, with 60 years or greater for optimal confidence (Guttman 1999; World Meteorological Organisation 2012). Calculations can be run with both estimated (<10% ideal) and missing data however the results can be affected, depending on its distribution within the record. Despite being regularly employed, research suggests that gamma distribution may not always be the best representation particularly of low precipitation environments (Guttman 1999; *SPI Generator* 2019).

With this in mind, gamma distribution will be used to estimate SPI given most readily available applications use this methodology.

The Gamma distribution is calculated as follows:

$$f(x, \alpha, \beta) = \frac{1}{\beta^{\alpha}\,\Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}}, \text{ for } x > 0$$

Where,

α is an estimated shape parameter corresponding to each station and time interval (1, 3, 6, 9, 12 months)

β is an estimated scale parameter corresponding to each station and time interval (1, 3, 6, 9, 12 months)

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right), \qquad \beta = \frac{\overline{x}}{\alpha} \text{ where } A = \ln(\overline{x}) - \frac{\sum \ln(\overline{x})}{n}$$

x is the observed precipitation amount

Γ(α) is the gamma function

n is the number of observations

(Equation 9 courtesy of Tigkas et al. (2013))

Cumulative distribution function is used to define the cumulative probability of an observed rainfall event occurring for a given month and time interval at each station.

$$F(x) = q + (1 - q)f(x, \alpha, \beta)$$

(Equation 10 courtesy of Tigkas et al. (2013))

Where q, the probability of zero precipitation, is equal to the number of observed zero rainfall events, m divided by the number of observations, n.
Each value is then transformed to standard normal variables to give the corresponding SPI (Tigkas et al. 2013).

3.5.3 Standardised Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010)

In an arid environment up to 90% of the annual precipitation is returned to the atmosphere via mechanisms of the hydrological cycle (Rodda 2011). SPEI employs extended climatic water balance theory to incorporate the evaporative demand into the original SPI calculation. Available soil moisture (D) can be estimated in terms of surplus or deficit by subtracting potential evapotranspiration (PET) from precipitation (P) for a specified residence time (i) as in,

$$D_i = P_i - PET_i$$

(Equation 11)

Actual evapotranspiration (AET) is the combined abstraction of water from available water by means of transpiration from plants and evaporation at the water surface or, as is often the case in dryland crops, the soil surface. Under this process soil moisture continues to be drawn from the available water supply until the wilting point is reached. To overcome the difficulty of field measurements a simplified potential evapotranspiration (PET) is estimated, often from meteorological data, by assuming an adequate water supply to a completely vegetated surface.

Due to the exceptionally limited record of temperature over the study region this study will revert to data available through Queensland Government's Long Paddock SILO portal for rainfall, temperature, and the corresponding estimate of PET. This portal provides several patched (temporally complete) data products based on spatially interpolated meteorological data validated against BoM's Australian Gridded Climate Data (Beesley et al. 2009). In this instance, PET derived by FAO's Penman-Monteith equation (Equation 12 courtesy of SILO (2020)) for short crops will be used as it allows for best replication of the seasonal variation associated with plant growth, making it more applicable to dryland farming (Allen et al. 1998).

$$\mathrm{ET_o} = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 1 + 0.34u_2)}$$

Where,

$\mathrm{ET_o}$ = reference evapotranspiration (mm/day)
R_n = net radiation at the crop surface (MJ/m²/day)
G = soil heat flux density (MJ/ m²/day)
T = air temperature at 2m height (⁰C)
u_2 = wind speed at 2m height (m/s) (default 2m/s assumed)
e_s = saturation vapour pressure (kPa)
e_a = actual vapour pressure (kPa)
$e_s - e_a$ = saturation vapour pressure deficit (kPa)
Δ = slope vapour pressure curve (kPa/⁰C)
γ = psychrometric constant (kPa/⁰C)

(Equation 12 courtesy of SILO (2020))

Plant growth is taken into account by applying a dimensionless crop coefficient, $\mathbf{K_c}$ to the measured crop evapotranspiration, $\mathbf{ET_c}$ (mm/d) (or, as in this case, estimate of PET provided by SILO). Where,

$$\mathrm{ET_c} = \mathrm{K_c}\,\mathrm{ET_o}$$

(Equation 13)

The crop coefficient, $\mathrm{K_c}$ accounts for the aggregated mechanism of the physical and physiological factors as the crop develops (see Figure 14). Due to the lack of actual available $\mathrm{K_c}$ data for the Northern Agricultural Region this study uses the following values in Table 6 based on the recommended winter wheat crop coefficients in the Mediterranean as outlined by the FAO Irrigation and Drainage Paper No. 56 to estimate $\mathrm{ET_c}$ (Allen et al. 1998). It is important to note that the true crop coefficient values for the North Midlands may widely differ from those adopted here and there are limited resources to substantiate the assumed values.

Table 6: Adopted Crop Coefficients

Stage	Initial	Development	Mid-Season	Late Season
Month	May	June	July/August	September
Adopted K_c	0.3	0.725	1.15	0.3

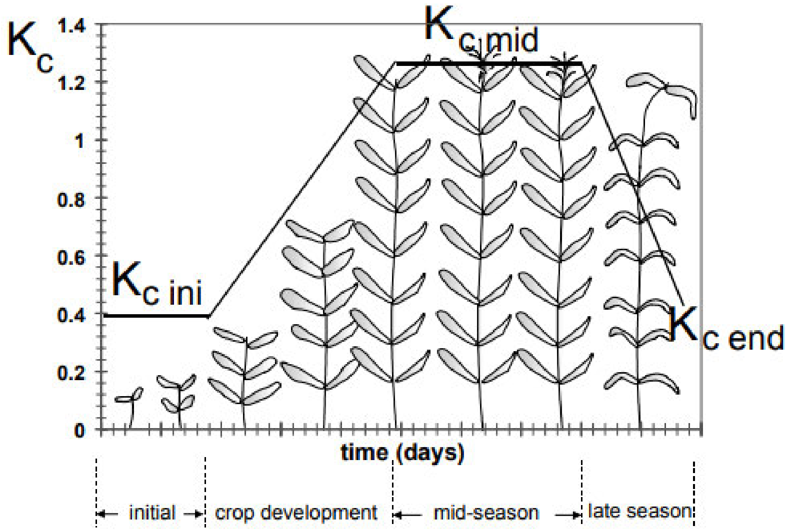

Figure 14: Influence of a single crop on evapotranspiration over time courtesy of Allen et al. (1998, p. 100)

It is also important to note that while the drought declaration with respect to SPEI is the same as outlined for the SPI previously, there are some differences in the methodology used to calculate the two indices. MATLAB®'s Climate Data Toolbox SPEI function employed in this study integrates SPEI over a specified residence period rather than calculating a rolling accumulated value for each month according to the residence period. A 6-month SPEI by this method therefore only calculates a value at every 6-month time interval. However, most importantly, this program uses a normal probability distribution rather than the gamma probability distribution used for SPI calculations in this study. As a result, the comparison of ability to declare drought under each methodology is not solely dependent on its representation of the water balance.

As such a one-sample Kolmogorov-Smirnov test (k-test) has been conducted in MATLAB® on the raw data at Windmere to indicate the impact of this on the estimated SPEI. This test is a parametric goodness-of-fit test used to determine the suitability of the distribution for modelling both the rainfall and temperature records used in this work. The test simply rejects the null hypothesis (H_o) if the is empirical not found to fit the chosen distribution to a significance level of 5%. The test statistic is calculated as follows:

$$D^* = \max_x(|F(x) - G(x)|)$$

Where,

$F(x)$ = the empirical (rainfall or temperature) distribution
$G(x)$ = the chosen distribution (normal or gamma)

(Equation 14 courtesy of MATLAB® (2020))

3.6 Interpolating Data and Graphical Representation

3.6.1 Kriging

Kriging is a geostatistical method that interpolates the surface of a spatial dataset based on the statistical relationship between points. Unlike deterministic methods, such as Spline and Inverse Distance Weighting (IDW), it considers both the distance and direction to develop a spatial correlation before estimating a corresponding weight for the measured values across the defined region.

$$\hat{Z}(s_o) = \sum_{i=1}^{N} \lambda_i Z\,(s_i)$$

Where,

N = the number of measured values
λ_i = an unknown weight for the measured value at the i th location
$Z(s_i)$ = the measured value at the i th location
s_o = the prediction location

(Equation 15 courtesy of ArcGIS Pro (2020))

Kriging most closely captures the pattern of rainfall variability given its predisposition to distance and directional influences. It is a complex approach made simple with the use of geographic information systems such as Esri ArcGIS, which firstly determines the statistical dependence through applications of variography allowing an empirical model to be developed that best represents the dependence of pairs of points in close range to one another. The ArcGIS kriging tool relies on the most appropriate selection of semi-variogram model (Figure 15), with each option 'designed to fit different types of phenomena more accurately' (*ArcGIS Pro* 2020).

Given the variable nature of meteorological conditions, an 'Ordinary' Kriging method employing the 'Spherical' semi-variogram model is run to the extent of the North Midlands Region for the purposes of this study. The semi-variogram is calculated according to the following,

$$\text{Spherical Variability, } \gamma(h) = \begin{cases} c_o + c\left(\frac{3h}{2a} + \frac{1}{2}\left(\frac{h^3}{a^3}\right)\right) & 0 < h \le a \\ c_o + c & h > a \\ 0 & h = a \end{cases}$$

Where,

h = distance between data points
a = range
c_o = nugget
c = partial sill

(Equation 16 courtesy of ArcGIS Pro (2020))

The semi-variogram plots the spatial autocorrelation between pairs of stations and provides an indication of the fit of the interpolated surface. The 6-month SPEI for June 2007, for example (Figure 16), shows a flattening of the curve or range at 0.69 degrees (approx. 75 kms) indicating that beyond this point the dataset is no longer spatially correlated. A positive nugget value results according to the degree of spatial variation over short distances with respect to the relatively widely spaced station locations.

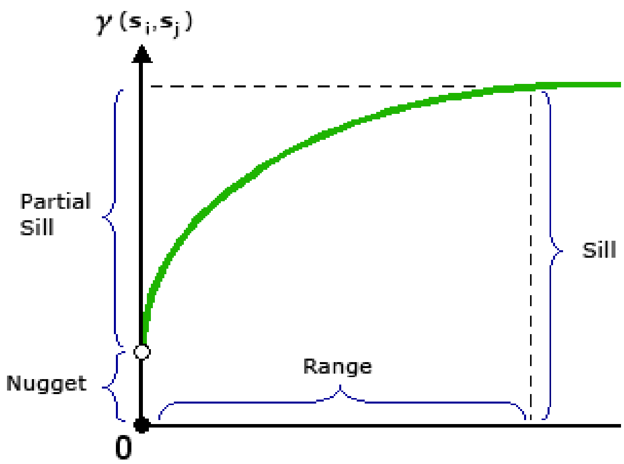

Figure 15: Illustration of Semi-variogram (*ArcGIS Pro* 2020)

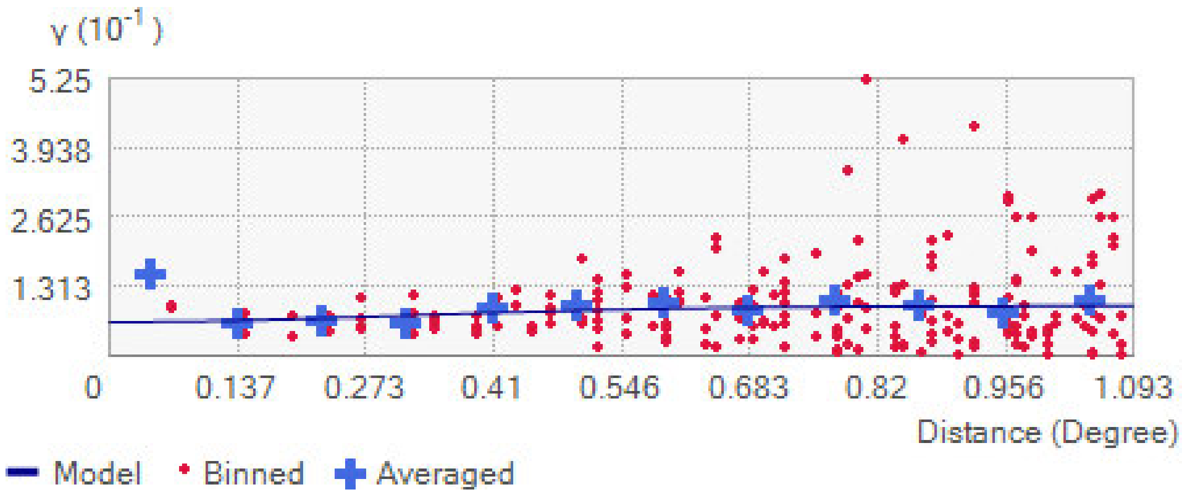

Figure 16: Semi-variogram Output for 6-month SPEI 2007 (*ArcGIS Pro* 2020)

3.7 Regression Analysis

3.7.1 Least Squares Linear Regression

Least Squares Linear Regression analysis has been adopted to determine the trend of the drought indices which show promise in comparison to anecdotal evidence. It is a commonly used parametric predictive modelling method that attempts to minimise the sum of the offsets between the estimated line of fit and actual data points to determine a discrete function of the variables. Once the relationship is derived (see (Equation 17), a forecast can be extrapolated. The equation takes the form:

$$y = bx + c$$

Where,

y = the drought index

x = time

b, the gradient $= \frac{\sum_{i=1}^{n}(x_i - \bar{x})\,(y_i - y)}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$

c, the y-intercept = $\bar{y}.b\bar{x}$

(Equation 17)

Several statistical performance measures can also be derived to explain the confidence of the regression model. Although dependent on the purpose of the model, a combination of the coefficient of determination (R^2), Root-mean-square-error (RMSE), and hypothesis testing are typically used to determine its reliability.

The R^2 is a measure of the strength of the fitted regression line to the actual data.

$$R^2 = \frac{\sum_{i=1}^{N}(\hat{y}_i - \bar{y}_i)}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}$$

Where,

N = number of data points

$\bar{y}_i$, mean value $= \frac{1}{N}\sum_{i=1}^{N} y_i$

y_i = observed value

$\hat{y}_i$ = forecasted value

(Equation 18 courtesy of MATLAB (2020))

For the purpose of forecasting, RMSE may be considered the most important criterion as it gives an indication of how concentrated the actual data points are around the fitted model, and therefore a low RMSE infers an accurate model. RMSE represents the standard deviation of variance unexplained by the model and is therefore given in the same units as the estimated value.

$$RMSE = \sqrt{\frac{SSE}{N}}$$

Where,

SSE, sum of squared errors $= \sum_{i=1}^{N}(y_i - \hat{y}_i)^2$

(Equation 19)

As before with the M-K test, hypothesis tests can be used to determine the statistical significance of the trend. Assuming an $\alpha = 0.05$ level of significance, the test statistic, T must be less than the critical value to reject the null hypothesis (H_0) of no relationship with 95% confidence, suggesting the trend is statistically significant. Alternatively, no statistically significant correlation between shifts in the drought indices with respect to time can be assumed. The critical values are according to the degrees of freedom and significance level outlined in the two-sided Student's t distribution table.

$$T\text{, test statistic } = \frac{b_1}{SE}$$

Where,

SE, standard error of the slope = $\frac{\sqrt{\sum(y_i - \hat{y}_i)^2 / n-2}}{\sqrt{\sum(x_i - \bar{x})^2}}$

b_1 = is the slope of the sample regression line

y_i = value of the dependent variable at observation i

$\hat{y}_i$ = estimated value of the dependent variable at observation i

x_i = the observed value of independent variable at observation i

$\bar{x}$ = the mean of independent variable

n = number of observations

(Equation 20)

3.7.2 Worsley Likelihood test

Past research by the CSIRO, and numerous others, into climate change has led to several widely adopted step changes resulting from a climate shift in the Southwest region (Charles et al. 2010). Typically, 1975 - 2000 and every decade period following are considered to have experienced significant drops to drier conditions and are often accepted for comparative analysis of rainfall trends. In an attempt to address this without making assumptions for the Northern Agricultural region, the case for step change is determined by a Worsley Likelihood test for each station using the trend tool in eWater's Water Quality Analyser 2.1.2.4.

The Worsley Likelihood test is a parametric test used to determine the likelihood of a step jump in the mean similarly to a Cumulative Deviation Test, however each value of cumulative deviation from the mean is weighted, S'_K according to their distribution in the time-series, as follows:

$$Z'_K = [k(n-k)]^{-0.5} S'_K$$

$$Z''_K = Z'_K / D_x$$

Where

W, the test statistic $= \frac{(n-2)^{0.5} V}{(1-V^2)^{0.5}}$

V = $\max|Z''_K|$

k = time interval

n = number of observations in the time-series

(Equation 21 courtesy of Tennakoon et al. (2011))

Table 7: Critical Values of W taken from Tennakoon et al. (2011)

N	W at significance level		
	α = 0.10	α = 0.05	α = 0.01
10	3.14	3.66	4.93
15	2.97	3.36	4.32
20	2.90	3.28	4.13
25	2.89	3.23	3.94
30	2.86	3.19	3.86
35	2.88	3.21	3.87
40	2.88	3.17	3.77
45	2.86	3.18	3.79
50	2.87	3.16	3.79

3.7.3 Long Short-Term Memory (LSTM) Network

Long Short-Term Memory is a recurrent neural network that is becoming increasingly used for regression analysis of time series data. It processes both individual data points and sequences within the dataset over arbitrary periods making it useful to model the variable influence of climate. This study explores the use of MathWorks® Deep Learning Toolbox available in MATLAB 2020a to train a LSTM (Figure 17) and forecast drought at Windmere based on the historical record.

The LSTM layer architecture (Figure 18) reveals the iterative process used to incrementally process the dataset X_t. At each time interval t, the cell A uses the current state of the network (c_{t-1}, h_{t-1}) and the subsequent time interval in sequence to calculate the output or hidden state, h_t and the new cell state c_t. Essentially, each of the cells draft which information is used, and which is left out, based on previous dependencies found in the dataset.

Figure 17: LSTM Training Progress Example for Windmere SPI

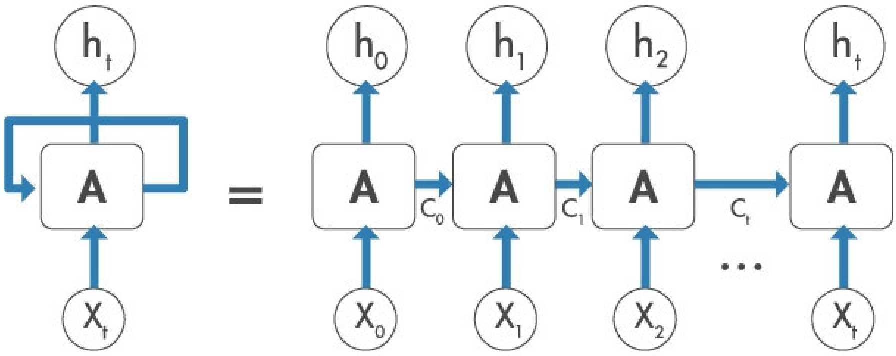

Figure 18: LSTM network architecture (*MATLAB* 2020)

4. RESOURCES

The rainfall data used in this study is readily available on the Bureau of Meteorology Climate Online database. Evapotranspiration data from Queensland Government's SILO database is also used as a supplement. Additional rainfall data is sourced from farm records and digitised before being validated against the closest BoM stations. The farm-based data and anecdotal accounts of their observations of climate over the past 40 years at Windmere is provided by Jan and Greg Waite. The transcript for this interview along with the monthly rainfall records is provided in Appendix A2 and A3, respectively.

To preserve flexibility in research and develop an understanding of the manipulations involved MathWorks® MATLAB 2019b/2020a is employed to conduct pre-processing, determine reliability, calculate all drought indices, and perform regression analysis. This involves running several functions scripted by others and downloaded from MathWorks® file exchange, as outlined in Table 8. The results were then imported into Esri ArcGIS Pro 2020 for spatial analysis and the Trend Analysis tool in eWater Water Quality Analyser v2.0.0 used to verify the statistical significance of the regression analysis.

Table 8: MATLAB code retrieved from MathWorks® online file exchange

Function	Version
ktaub.m	Mann-Kendall Tau-b with Sen's Method (enhanced) version 1.15.0.0 (37 KB) by Jeff Burkey
sktt.m	Seasonal Kendall Test with Slope for Serial Dependent Data version 1.9.0.0 (13.1 KB) by Jeff Burkey
SPI.m	Standardized Precipitation Index version 1.0.0.0 (1.54 KB) by Taesam Lee
SPEI.m	Available in MATLAB Climate Data Toolbox version 1.01 (107MB) by Chad Greene
Deep Learning Toolbox	Time Series Forecasting Using Deep Learning example accessed 6 September 2020 https://au.mathworks.com/help/deeplearning/ug/long-short-term-memory-networks.html

Other code written by the author for this work is included in Appendix A4.

5. ANALYSIS

5.1 Reliability

Based on the correlation between the record at Windmere and Minaru in Table 9-11, with 204.7 mm and 209 mm mean growing period rainfall respectively, it can be assumed that the farm-based data is reliable and there are no significant outliers or errors. It has been found that there are no significant trends for all periods other than the month of September at Minaru and Windmere, while Carnamah also experienced a statistically significant decrease in June rainfall for the period 1977 to 2014 (see Figure 19). September represented a period of statistically significant increase across all three stations. This is given by a critical M-K test trend score $-1.96 \geq Z \geq +1.96$ or significance (α) below 0.05, adopting a 5% tolerable probability that the trend is falsely rejected. Taking the impact of localised rainfall variability and strong gradient in rainfall to the north-east into consideration these results are concurrent with expectations.

Table 9: Statistics for Windmere between 1977 and 2014

Windmere 116.28°E, 29.85°S										
Time Series	**Mean (mm)**	**Median (mm)**	**Max (mm)**	**Min (mm)**	**St Dev.**	**Coef. Var**	**Mann-Kendall trend**	**Signific. (α)**	**Mann-Kendall Tau**	**Sen's Slope**
Jan	13.4	2.5	106.0	0.0	25.0	186.7	0.943	0.346	0.102	0.000
Feb	15.5	5.5	98.8	0.0	23.2	149.5	0.540	0.589	0.060	0.000
Mar	17.4	8.0	123.8	5.3	28.8	166.1	0.432	0.666	0.048	0.000
Apr	18.5	9.4	90.3	0.0	21.0	113.5	-0.063	0.950	-0.007	0.000
May	46.7	39.9	173.0	5.3	35.7	76.5	0.855	0.393	0.097	0.275
Jun	44.6	45.5	107.3	3.0	23.6	53.0	-1.848	0.065	-0.209	-0.633
Jul	49.9	47.4	101.8	12.5	24.2	48.5	0.515	0.606	0.058	0.200
Aug	39.1	34.4	97.8	12.3	21.5	55.0	0.126	0.900	0.014	0.053
Sep	24.5	24.8	63.8	0.0	12.2	49.7	2.917	0.004	0.330	0.475
Oct	12.2	10.1	49.8	0.0	10.7	88.1	0.050	0.960	0.006	0.000
Nov	9.9	5.9	106.0	0.0	25.0	186.7	0.444	0.657	0.050	0.000
Dec	9.8	5.4	40.5	0.0	10.9	111.0	0.256	0.798	0.028	0.000
Annual (J-D)	301.3	310.0	556.5	136.8	86.0	28.5	0.365	0.715	0.041	0.500
Winter (JJA)	133.6	127.5	227.5	54.3	41.3	30.9	-0.704	0.481	-0.080	-0.525
Growing Period (M-S)	204.7	192.6	382.3	96.3	60.6	29.6	0.792	0.428	0.090	0.570

Table 10: Statistics for Minaru between 1977 and 2014

Minaru 116.23°E, 29.85°S										
Time Series	**Mean (mm)**	**Median (mm)**	**Max (mm)**	**Min (mm)**	**St Dev.**	**Coef. Var**	**Mann-Kendall trend**	**Signific. (α)**	**Mann-Kendall Tau**	**Sen's Slope**
Jan	14.8	4.0	125.0	0.0	27.3	184.3	1.170	0.242	0.128	0.000
Feb	13.4	5.0	71.8	0.0	17.3	128.7	0.051	0.959	0.006	0.000
Mar	18.4	8.3	118.8	4.0	27.1	147.1	0.843	0.399	0.095	0.130
Apr	19.0	13.8	89.8	0.0	20.1	106.2	-0.440	0.660	-0.050	-0.111
May	46.2	40.1	167.8	4.0	34.6	74.8	0.214	0.831	0.024	0.059
Jun	45.4	42.4	109.6	3.0	25.0	55.0	-1.345	0.178	-0.152	-0.563
Jul	52.9	48.3	121.6	11.0	27.5	52.0	0.151	0.880	0.017	0.092
Aug	38.7	32.7	101.8	12.0	20.5	53.1	-0.101	0.920	-0.011	-0.021
Sep	25.8	26.3	54.2	5.4	11.5	44.8	1.974	0.048	0.223	0.369
Oct	14.6	10.0	108.2	0.0	18.5	126.3	-0.415	0.678	-0.047	-0.050
Nov	10.4	5.5	125.0	0.0	27.3	184.3	0.177	0.860	0.020	0.000
Dec	12.3	6.4	52.6	0.0	14.7	119.2	-0.089	0.929	-0.010	0.000
Annual (J-D)	312.0	306.6	550.0	177.6	80.2	25.7	-0.264	0.792	-0.030	-0.438
Winter (JJA)	137.1	140.3	227.6	52.2	42.7	31.1	-0.905	0.365	-0.102	-0.575
Growing Period (M-S)	209.0	199.9	366.2	114.0	58.4	28.0	0.264	0.792	0.030	0.347

Table 11: Statistics for Carnamah between 1977 and 2014

Carnamah 115.89°E, 29.69°S										
Time Series	**Mean (mm)**	**Median (mm)**	**Max (mm)**	**Min (mm)**	**St Dev.**	**Coef. Var**	**Mann-Kendall trend**	**Signific. (α)**	**Mann-Kendall Tau**	**Sen's Slope**
Jan	13.5	2.4	151.6	0.0	27.0	199.0	0.093	0.926	0.011	0.000
Feb	14.1	6.3	82.5	0.0	19.4	138.0	-1.070	0.285	-0.121	-0.086
Mar	15.3	8.2	77.9	6.0	19.7	128.9	0.805	0.421	0.091	0.093
Apr	20.5	13.7	78.0	0.0	20.1	98.0	-0.943	0.346	-0.107	-0.200
May	49.7	42.5	182.1	6.0	37.6	75.7	0.352	0.725	0.040	0.130
Jun	55.4	53.8	124.2	2.2	28.5	51.5	-2.238	0.025	-0.253	-1.037
Jul	58.1	55.2	107.5	9.4	26.4	45.5	-0.176	0.860	-0.020	-0.108
Aug	46.7	40.2	99.2	8.2	22.4	48.0	-0.792	0.428	-0.090	-0.213
Sep	26.8	26.5	53.7	5.7	12.9	47.9	2.037	0.042	0.230	0.429
Oct	13.5	11.0	55.0	0.8	12.0	88.7	-0.893	0.372	-0.101	-0.122
Nov	11.3	7.1	151.6	0.0	27.0	199.0	-0.406	0.685	-0.047	-0.016
Dec	10.9	6.1	41.2	0.0	11.9	109.8	-0.592	0.554	-0.067	-0.047
Annual (J-D)	335.1	325.3	594.7	202.3	88.0	26.2	-1.773	0.076	-0.201	-2.583
Winter (JJA)	160.2	149.5	287.7	59.5	49.2	30.7	-1.823	0.068	-0.206	-1.258
Growing Period (M-S)	236.8	245.1	412.4	131.4	63.5	26.8	-1.094	0.274	-0.124	-1.063

Note: Carnamah missing data for Nov 2003 and Jan 2008

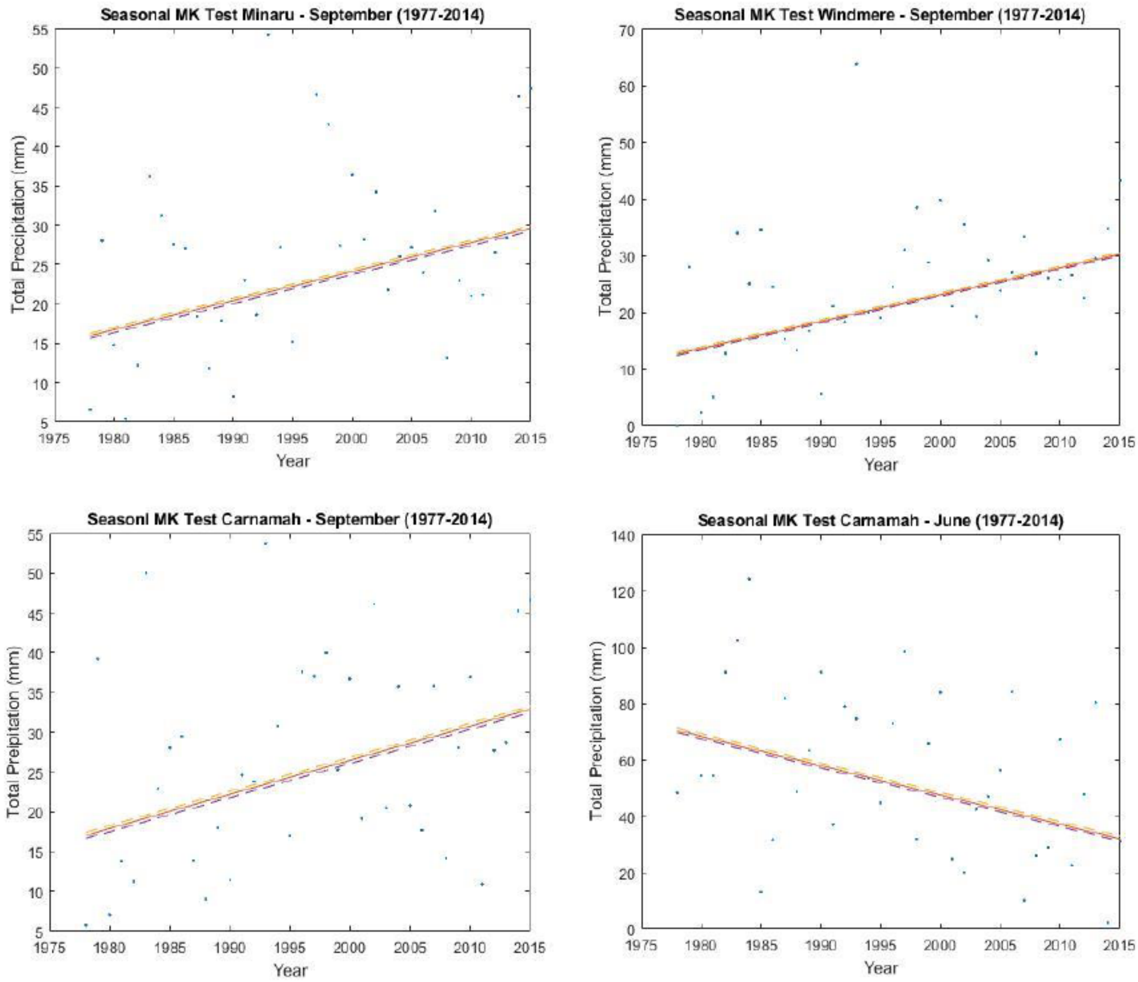

Figure 19: M-K test trends of significance

5.2 Deciles

The growing period deciles calculated at Windmere station support anecdotal evidence of dry years most reliably with most severe years detected, including 1977, 1979, 2002, and 2007 (see Figure 20). On the other hand, the quarterly and annual deciles have over and underestimated the occurrence of drought, respectively. The winter decile appears to be completely unreliable in estimating both the occurrence and severity of drought. Most valuably, the growing period deciles of a seasonal crop are unlikely to be influenced drastically by the previous season and as a result the lack of specified drought duration by deciles has minimal limitations on its use in this respect.

The downside, however, is that deciles lack consideration of crop growth, which once germinated is increasingly influenced by humidity and temperature. With increased water requirements, a dry August such as in 2006, was understandably accounted as a drought by grain growers despite not registering as a serious rainfall deficiency according to growing period deciles. Although not reaching drought status in this context, 2006 was estimated as a poorer year, consistent with anecdotal accounts. Altering the threshold for drought classification or reviewing the deciles at a shorter residence time within the historical record of all growing periods would likely replicate years of reduced viability more closely. Incorporation of temperature deciles would also likely improve this outcome as the impact of warm periods currently fails to be captured. Consequently 1994 and 2019 register as median years despite recording some of the warmest winter months on record and being accounted as droughts anecdotally.

A comparison of the adjusted May to September (Figure 21) growing period to the traditionally adopted May to October (Figure 22) period finds no impact on the years which fall within the Decile 1 and Decile 2 bands at Windmere with both periods capturing the worst years but also the same below average 'non-drought' years. However, the increased spread, particularly of the decile 2 band for the May to September growing period indicates a refinement in the classification using this method (see Figure 23). This can be seen with 2017 shifting incrementally closer to being reclassified as a year of serious rainfall deficit, while 2012, regarded as a 'non' drought year, advanced towards the third band. The lowest 10% of rainfall on record (band 1), below 128.4mm and 134.4mm captured serious rainfall deficiency equally for the May to September and May to October periods, respectively. Notably, drought classification under this threshold makes no allowance for negative terms of trade given anecdotal evidence suggests that 125mm of growing period rainfall is required merely for a viable crop.

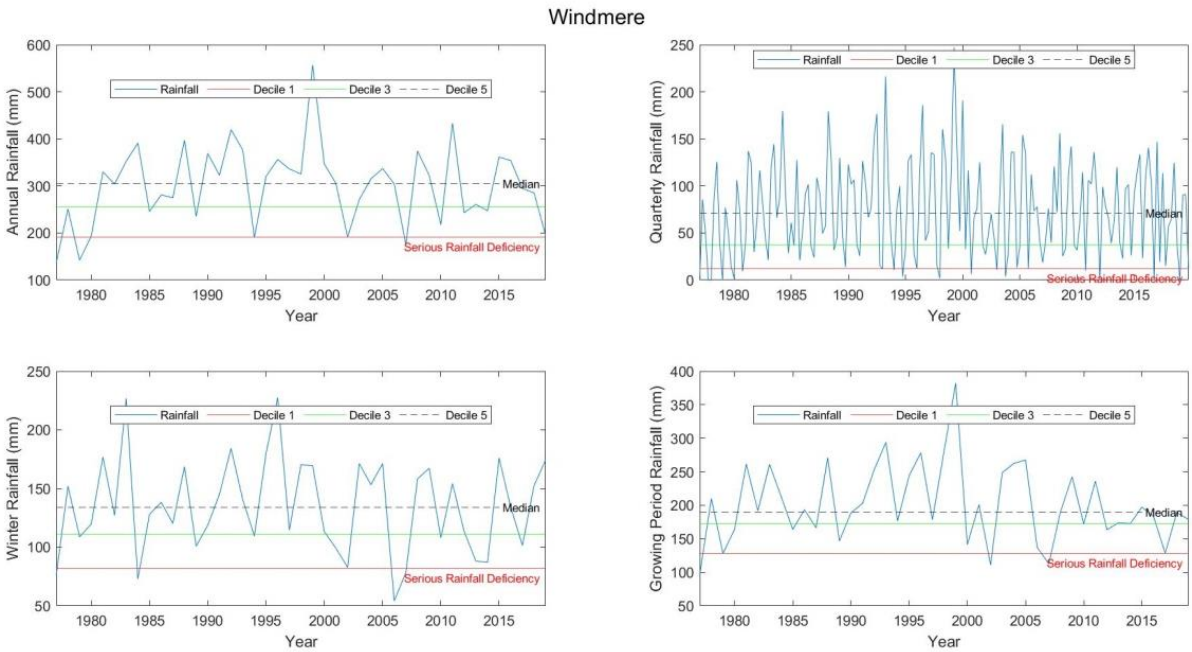

Figure 20: Windmere Deciles Index

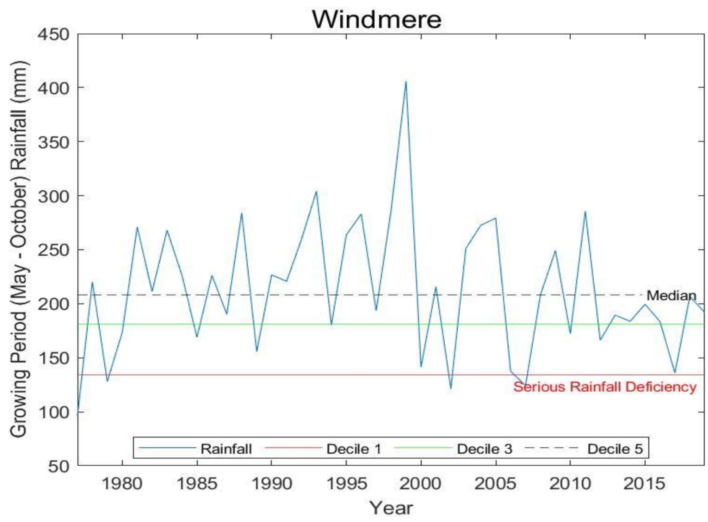

Figure 21: Adjusted Growing Period May to September

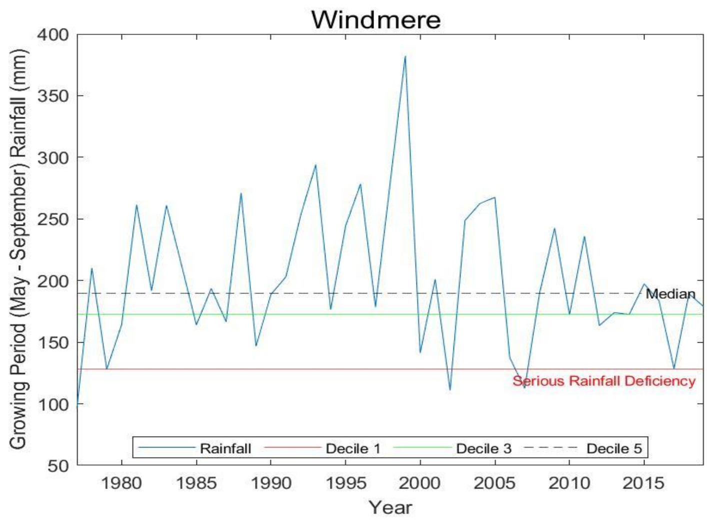

Figure 22: Traditional Growing Period May to October

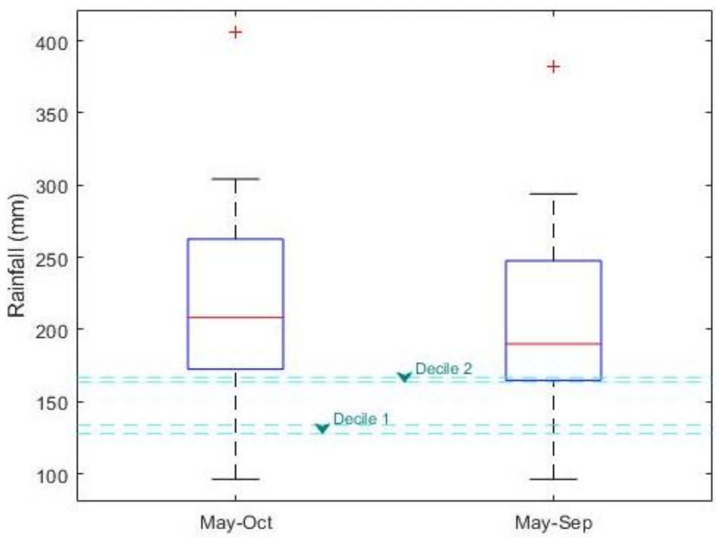

Figure 23: Comparison of Growing Period Rainfall at Windmere

Windmere recorded a decile 1 growing period in 2007, whilst 2006 was a marginally better year, registering as a decile 2, which is clearly represented by the graphics in Figure 24 and Figure 25, respectively. On the other hand, anomaly maps, produced by the BoM, of rainfall deciles for the 6 months to October, show the widespread prevalence of drought conditions in 2006 (see Figure 26), however fails to capture the same degree of areal variability with respect to the conditions of 2007 (see Figure 27) in the North Midlands. This highlights the importance of locality specific drought classifications and methods.

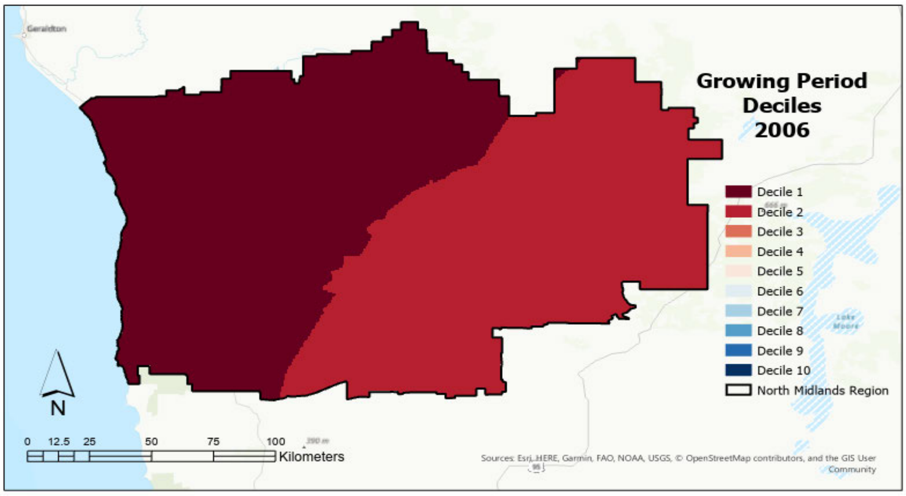

Figure 24: Rainfall Deciles (May - September) for North Midlands for 2006

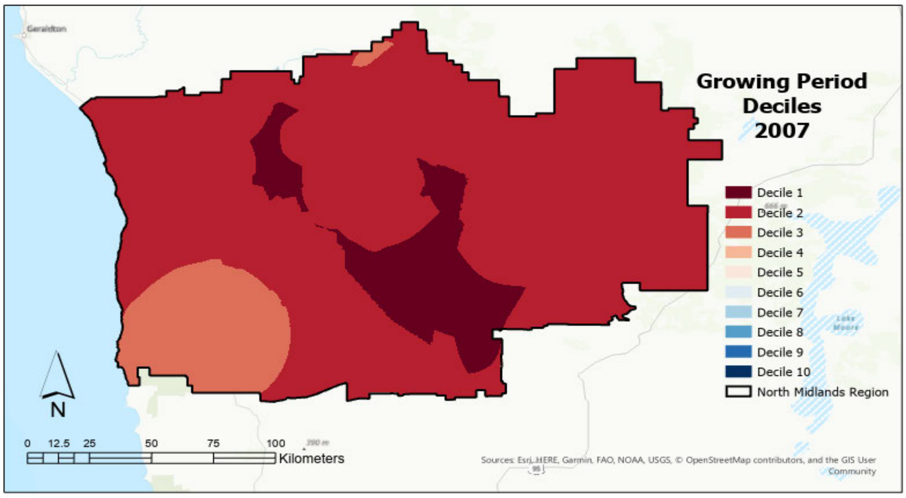

Figure 25: Rainfall Deciles (May - September) for North Midlands for 2007

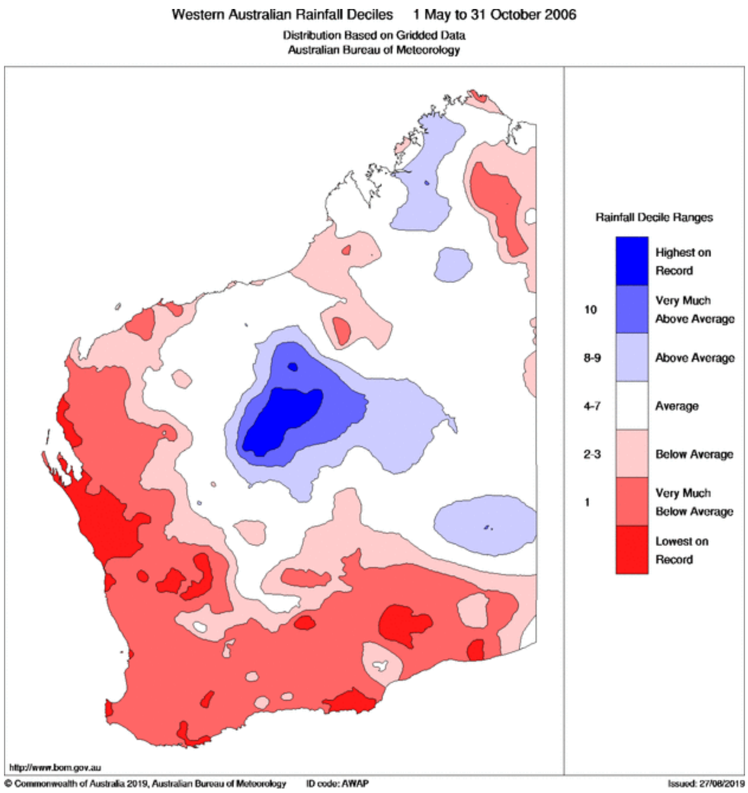

Figure 26: Rainfall Deciles (May – October) (Climate Data Online 2020)

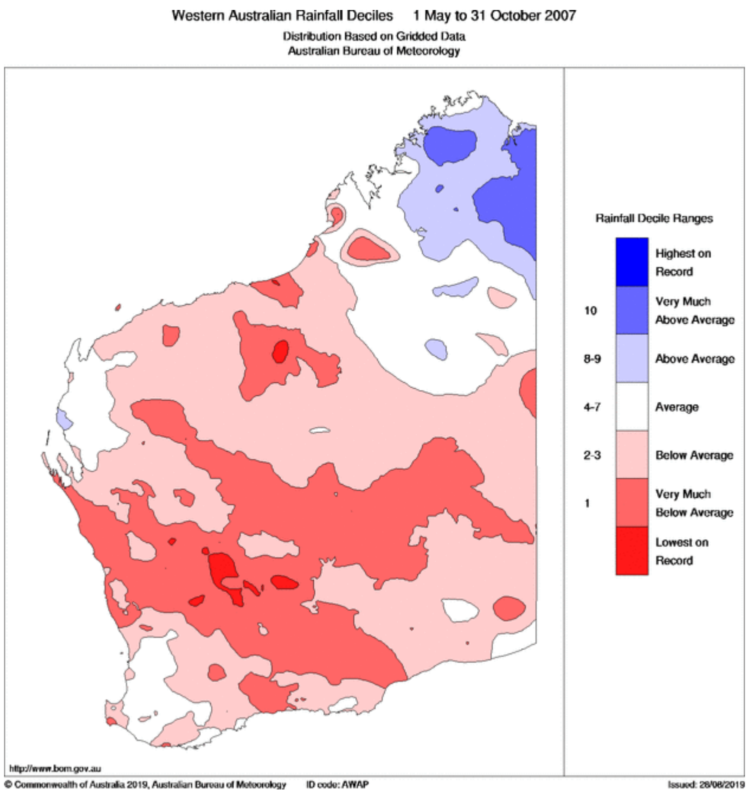

Figure 27: Rainfall Deciles (May – October) (Climate Data Online 2020)

5.3 Standardised Precipitation Index

As recommended by McKee et al. (1993) the moving timescale of 3-month SPI best replicates the drought conditions at Windmere when compared with other SPI residence times (see Figure 28). However, there are several occasions including May 1985 - September 1985 and February 2012 - November 2012 which record as drought, however, are inconsistent with anecdotal evidence. This is possibly due to only minimal interference with the growing period in terms of both duration and severity. The 1989 growing period, for instance, experienced below average rainfall – registering only 146.75mm – however it was not considered an extremely dry or deficient rainfall year by grain growers despite the 3-month SPI dipping severely to -2.7 by September. This is a result of the early onset of dry summer conditions at the end of 1989 which, despite placing pressure on bore water availability and rainwater supplies, had limited repercussions for the viability of the winter crop which likely matured on subsoil moisture.

Furthermore, despite 2007 recording as the worst year on record at Windmere it only just meets the threshold for drought by this method reaching -1.64 at worst. It does however have the longest sustained period of SPI below -1.0, giving an indication of the role of duration in drought classification. This period would certainly relate to the hardships of failed crops and loss of livestock experienced in 2007. Defining the duration is evidently a useful concept given the ability to adapt SPI thresholds to characterise drought in relation to a growing period. This may also be useful when considering SPI does not account for intense periods of rainfall and the associated loss due to runoff.

For the purpose of characterising drought in the North Midlands Regions it is potentially more useful to define two separate conditions with either satisfied to trigger drought classification. This would allow the influence of variable rainfall distribution, in terms of severity and duration, on the growth of the crop to be accounted for regardless of the total rainfall. The first condition being a period of 3-month SPI equal to or below -0.60 for a minimum of four individual months during the growing period or alternately, a sustained period equal to or below -1.0 and not returning to a positive value for a minimum of 4 months during the growing period. Despite the improvements of defining drought, this method continues to capture 1985 as a drought year and omit 2019, however given each of these years experienced near adequate growing period rainfall neither would have been considered as a drought anecdotally based purely on rainfall.

Evidently, there are several influences including terms of trade and operational improvements that alter the overall outlook of a season. Importantly, SPI also neglects the influence of other meteorological conditions, such as humidity and temperature, and in situ characteristics, such as soil composition, on the overall crop water availability and demand. Nonetheless, the 3-month SPI as it currently stands does characterise poorer years where severe pressure is placed on agriculture in the North Midlands Region (see Figure 29).

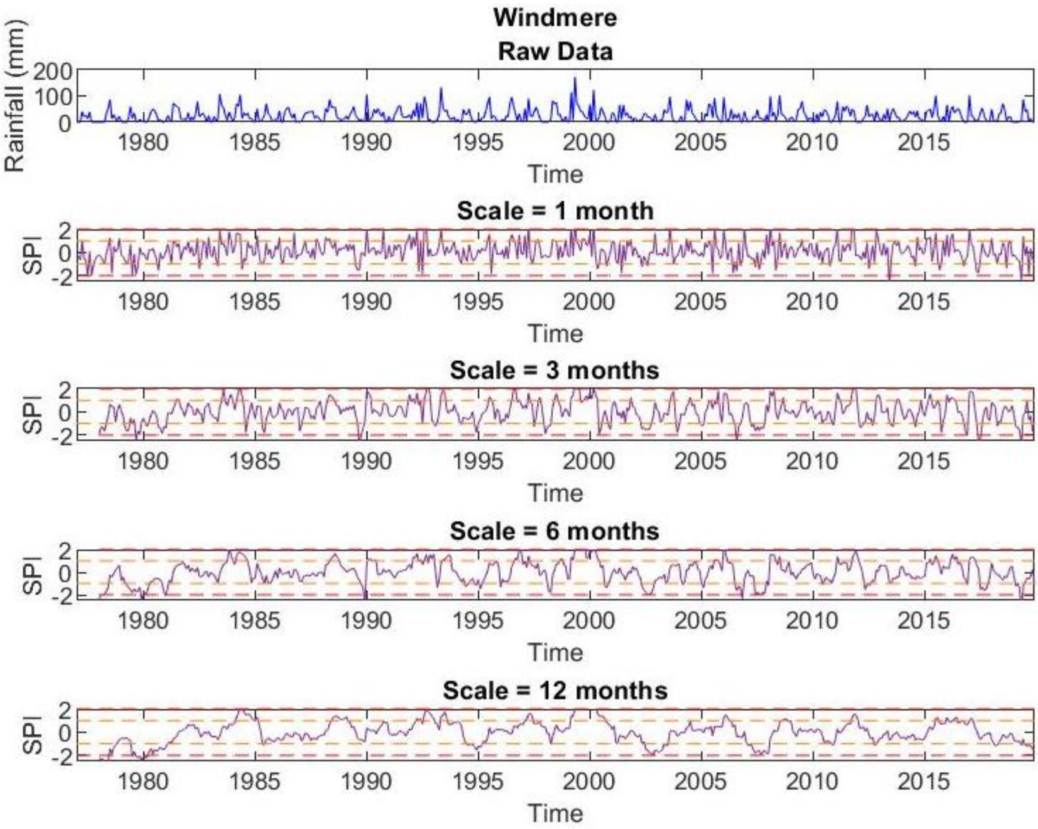

Figure 28: Windmere SPI Index

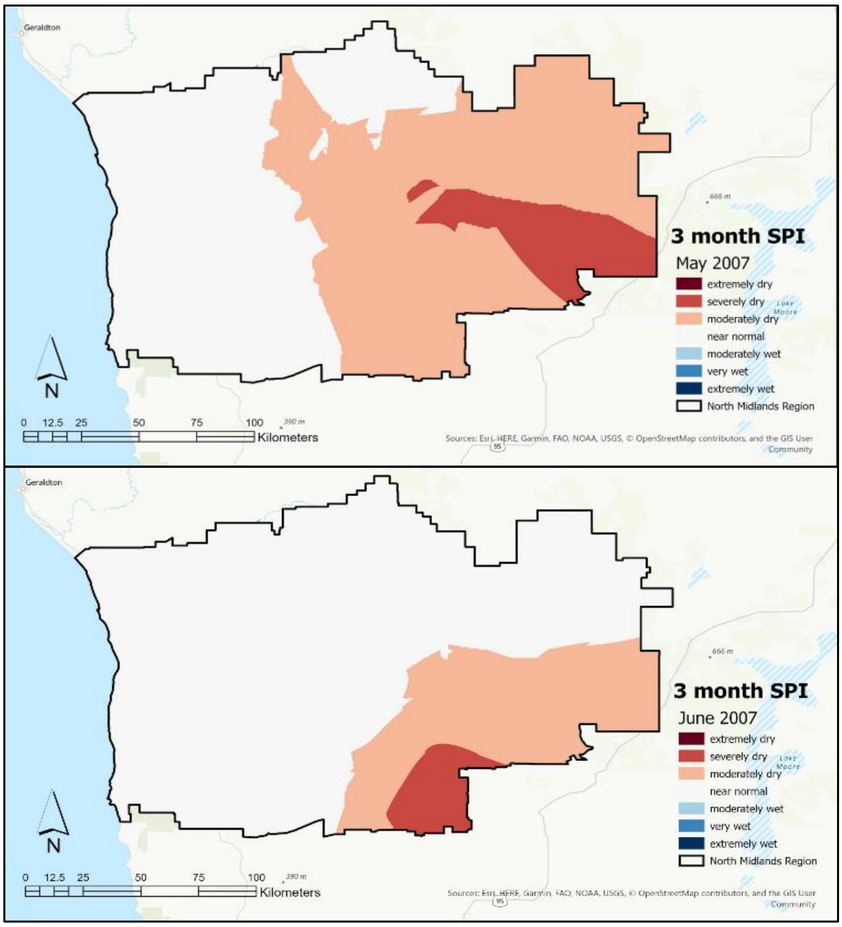

Figure 29: 3-month SPI for May & June 2007

5.4 Standardised Precipitation-Evapotranspiration Index

In this study the longer residence time of 6 months smooths the seasonal variation of the hot, dry summers evident in the evapotranspiration (see Figure 30) ensuring a more accurate characterisation of drought when compared to other residence times at Windmere. However, SPEI consistently fails to classify drought periods across all residence times in the North Midlands with respect to anecdotal drought years, particularly in the most recent decade. This may be a result of the assumptoin of normally distributed rainfalls, reliance on patched data and estimated crop coefficients leading to poorly derived values for SPEI.

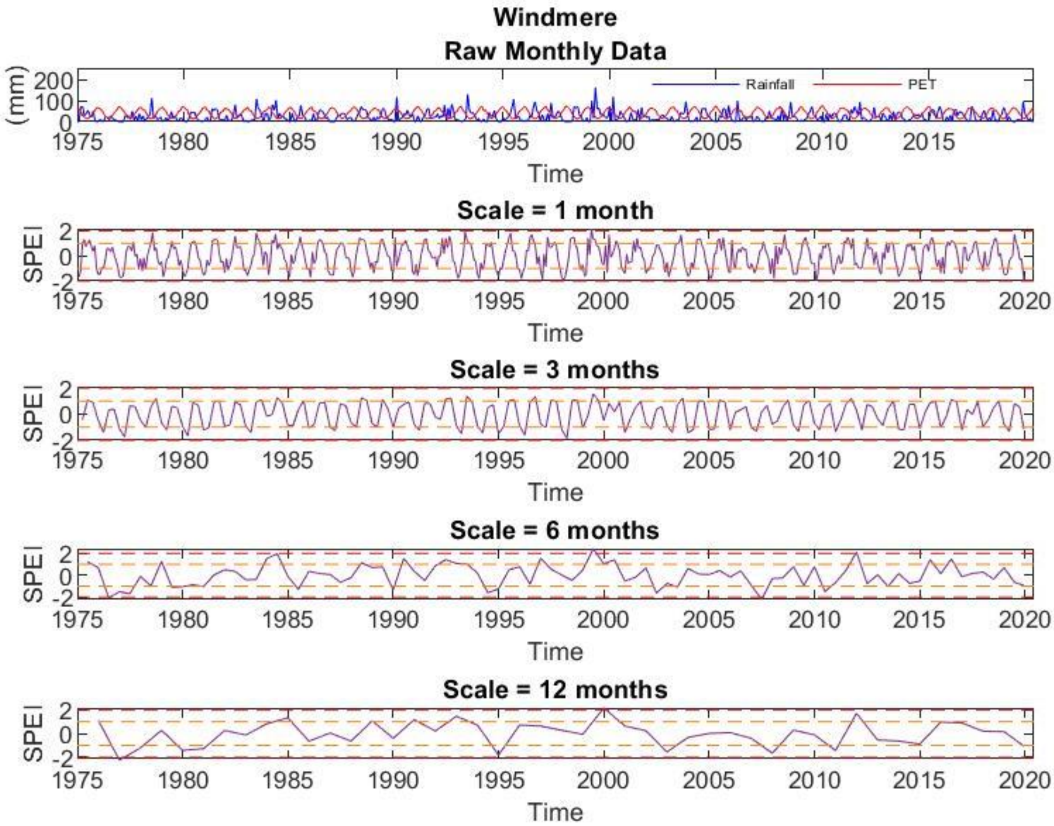

Figure 30: Windmere SPEI based on FAO56

The k-test rejects the suitability of the normal distribution for use in modelling both rainfall and temperature at Windmere (see Figure 31 & Figure 32). Unsurprisingly, despite neither gamma nor normal distributions being considered suitable by this test, there is stronger evidence to reject the suitability of the normal model with a smaller p-value, $1.507e^{-13}$, as oppose to $1.080e^{-12}$ for gamma as used in the SPI methodology at Windmere. Taking into consideration the minor discrepancy between the location of SILO's closest grid centroid and Windmere's actual rain gauge location, SILO clearly represents actual climatic conditions at Windmere well, as seen when comparing the distribution in Figure 32 and Figure 33. Unfortunately, the SPEI calculated by this method is unreliable.

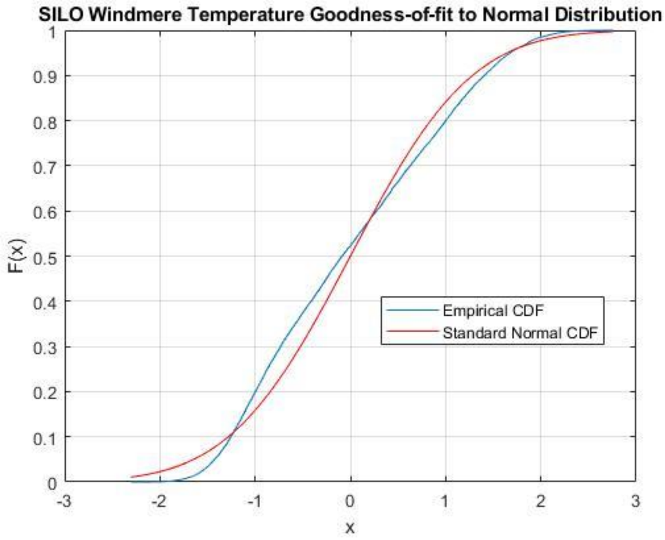

Figure 31: Windmere SILO Maximumm Temperature Cumulative Distribution

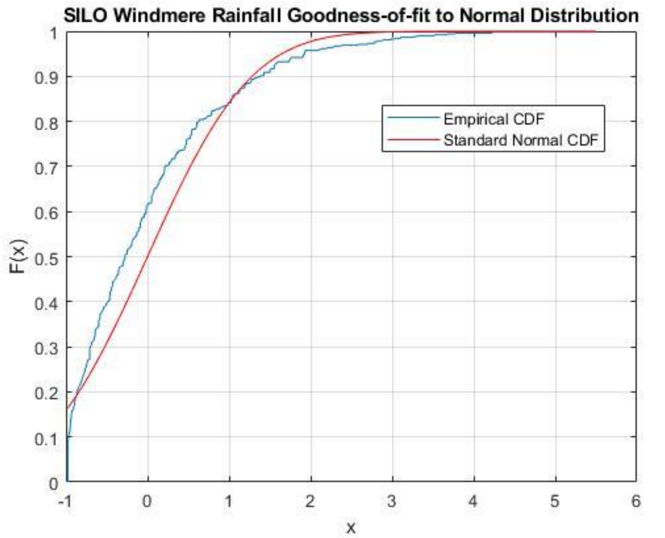

Figure 32: Windmere SILO Rainfall Cumulative Distribution

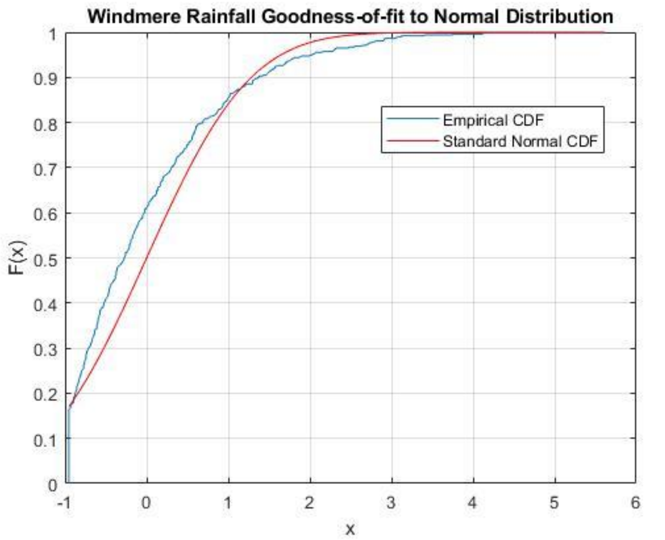

Figure 33: Windmere Rainfall Cumulative Distribution

Even so, the SPEI for June 2006 and 2007 shown in Figure 34 exposes some value in this method when compared with the growing period deciles of the same year. Given the dependence on rainfall for dryland farming, improved incorporation of the losses due to evapotranspiration for a more accurate representation of the crop water balance will inevitably develop more reliable drought indices for the future. This will likely require better coverage of not only temperature, but other climatic and environmental influences of water efficiency.

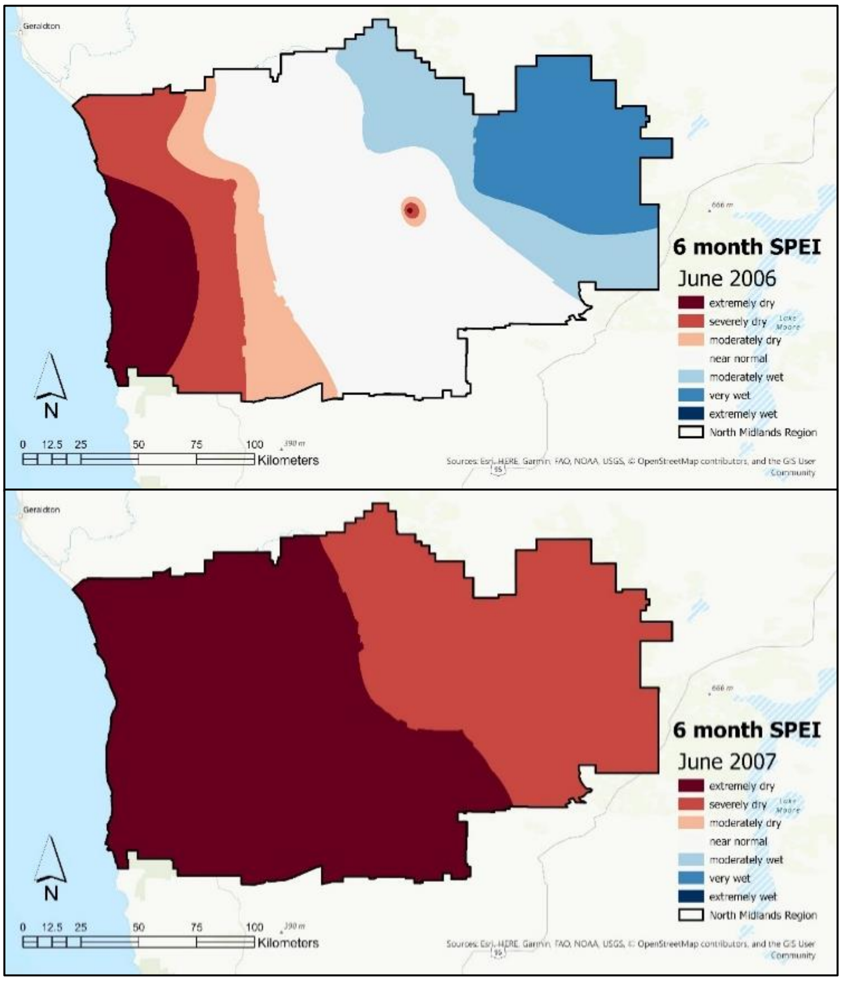

Figure 34: 6 Month SPEI for June 2006 and 2007

5.5 Analysis

5.5.1 Regression Analysis

Analysis of the indices has produced several significant results although often contradictory to one another. As such there is often no clear projection (see Table 12). Importantly, the Worsley Likelihood test found a significant number of stations experiencing a step jump both at the tails of the time-series and around the year 2000 suggesting findings by the CSIRO regarding changes as a result of climatic shift likely extend to study region. An extension of this work by removing data where step jumps were found at the tails and an analysis of their spatial occurrence would, however, be required to confirm this.

For Windmere, the Worsley Likelihood test found no statistically significant step jumps for the Growing Period Deciles, however SPI resulted in a statistically significant ($\alpha<0.01$) jump in 1981 and again in 2017 with a W-statistic (>3.81) of 5.735 and 3.864, respectively. With both step jumps falling within 5 years of the record extent there is potential that these periods are influenced by events beyond the historical record covered in this study and as such are not considered in this regression analysis.

Like more than 25% of the study area, both Growing Period DI and the 6-month SPEI at Windmere showed no significant linear trend. The 3-month SPI, on the other hand, consistently produced statistically significant trends across all stations. Logically, despite the 3-month SPI at Windmere producing very strong evidence for a trend with a significant level of $\alpha = 0.01$, a very low R^2 suggests the degree of variability in the index is poorly modelled by the linear relationship. Despite the poor confidence in the linear model across the study area, the 3-month SPI at Windmere (Figure 35) also produced an anomaly of a relatively unchanged, although positive outlook (highlighted in green in Table 12). More than 80% of all stations were found to have a statistically significant negative trend in 3-month SPI.

Table 12: Regression Analysis of Drought Indices

Station Name	Drought Index	statistic	t-statistic	alpha	critical value	Worley Likelihood α≥0.05
Arena	Growing Period Deciles	0.043	-2.121	0.05	2.727	
	3-month SPI	0	-38.428	0.01	2.601	2000
Canna	Growing Period Deciles	0.01	-3.032	0.01	2.633	1974
	3-month SPI	0	-38.102	0.01	2.576	2019
Carnamah	Growing Period Deciles	0.006	-3.959	0.01	2.617	1968
	3-month SPI	0	-34.459	0.01	2.576	2018
Coorow	Growing Period Deciles	0.009	-3.326	0.01	2.629	2005
	3-month SPI	0	-24.219	0.01	2.576	1913
Dongara	Growing Period Deciles	0.006	-3.937	0.01	2.617	1968
	3-month SPI	0	-23.759	0.01	2.576	2018
Eneabba	Growing Period Deciles	0.026	-2.701	0.01	2.682	
	3-month SPI	0	-38.275	0.01	2.595	2000
Fairfield	Growing Period Deciles	0.012	-4.181	0.01	2.646	1968
	3-month SPI	0	-38.514	0.01	2.576	2018
Five Gums	Growing Period Deciles	0.016	-3.043	0.01	2.654	1999
	3-month SPI	0	-33.38	0.01	2.583	2000
Green Grove	Growing Period Deciles	0.018	-2.83	0.01	2.658	1999
	3-month SPI	0	-45.745	0.01	2.586	2000
Hakea	Growing Period Deciles	0.008	-2.969	0.01	2.625	1968
	3-month SPI	0	-25.708	0.01	2.576	1918
Highfields	Growing Period Deciles	0.02	-2.822	0.01	2.662	1999
	3-month SPI	0	-30.498	0.01	2.588	2018
Irwin House	Growing Period Deciles	0.044	-3.267	0.01	2.745	1998
	3-month SPI	0	-37.136	0.01	2.602	1992
Koobabbie	Growing Period Deciles	0.009	-2.1	0.05	1.985	
	3-month SPI	0	-2.557	0.01	2.576	2018
Latham	Growing Period Deciles	not statistically significant				
	3-month SPI	0	3.051	0.01	2.576	
Leeman	Growing Period Deciles	0.035	-5.94	0.01	2.756	2005
	3-month SPI	0	-37.906	0.01	2.605	2000
Mallee Vale	Growing Period Deciles	not statistically significant				
	3-month SPI	0	9.756	0.01	2.579	1936
Manarra	Growing Period Deciles	0.01	-3.211	0.01	2.636	1998
	3-month SPI	0	-9.335	0.01	2.576	
Mellenbye	Growing Period Deciles	not statistically significant				
	3-month SPI	0	16.575	0.01	2.576	1996

Table 12 continued: Regression Analysis of Drought Indices

Minaru	Growing Period Deciles	not statistically significant				
	3-month SPI	0	26.072	0.01	2.578	1933
Mindarra	Growing Period Deciles	not statistically significant				
	3-month SPI	0	-5.481	0.01	2.6	2012
Mingenew	Growing Period Deciles	0.007	-3.925	0.01	2.618	1968
	3-month SPI	0	-11.315	0.01	2.576	2018
Morawa	Growing Period Deciles	0.009	-1.862	0.1	1.661	1999
	3-month SPI	0	-27.842	0.01	2.576	2019
Nindethana Farm	Growing Period Deciles	0.035	-2.522	0.05	2.021	1999
	3-month SPI	0	-14.243	0.01	2.6	2019
Oaklands	Growing Period Deciles	not statistically significant				1998
	3-month SPI	0	-22.969	0.01	2.603	2001
Perangery	Growing Period Deciles	0.011	-1.668	0.1	1.664	
	3-month SPI	0	-46.245	0.01	2.576	1935
Perenjori	Growing Period Deciles	0.011	-2.595	0.05	1.99	1999
	3-month SPI	0	-36.654	0.01	2.576	2001
Pindawa	Growing Period Deciles	not statistically significant				
	3-month SPI	0	2.152	0.05	1.966	2019
South Holmwood	Growing Period Deciles	not statistically significant				1999
	3-month SPI	0	24.135	0.01	2.576	1923
Strawberry North	Growing Period Deciles	0.008	-1.98	0.1	1.66	
	3-month SPI	0	-5.805	0.01	2.576	1903
Three Springs	Growing Period Deciles	0.008	-3.134	0.01	2.626	1933
	3-month SPI	0	-22.163	0.01	2.576	2018
Twin Hills	Growing Period Deciles	not statistically significant				
	3-month SPI	0	-14.783	0.01	2.605	1973
Wanarra	Growing Period Deciles	not statistically significant				
	3-month SPI	0	-3.787	0.01	2.598	
Warradage	Growing Period Deciles	0.051	-2.073	0.05	2.042	
	3-month SPI	0	-18.227	0.01	2.602	
Windmere	Growing Period Deciles	not statistically significant				
	3-month SPI	0	4.611	0.01	2.599	1981
Yandanooka	Growing Period Deciles	0.008	-4.964	0.01	2.625	1933
	3-month SPI	0	-40.425	0.01	2.576	2018
Yarragadee	Growing Period Deciles	0.01	-1.873	0.1	1.663	1998
	3-month SPI	0	-36.119	0.01	2.576	2000
Yongarloo	Growing Period Deciles	0.019	-2.002	0.05	1.999	1975
	3-month SPI	0	-15.446	0.01	2.584	2018
Ytiniche	Growing Period Deciles	0.01	-2.104	0.05	1.987	
	3-month SPI	0	-25.123	0.01	2.576	2018

Note: 6-month SPEI is not included in this table due to vast numbers of stations resulting in no statical significance.

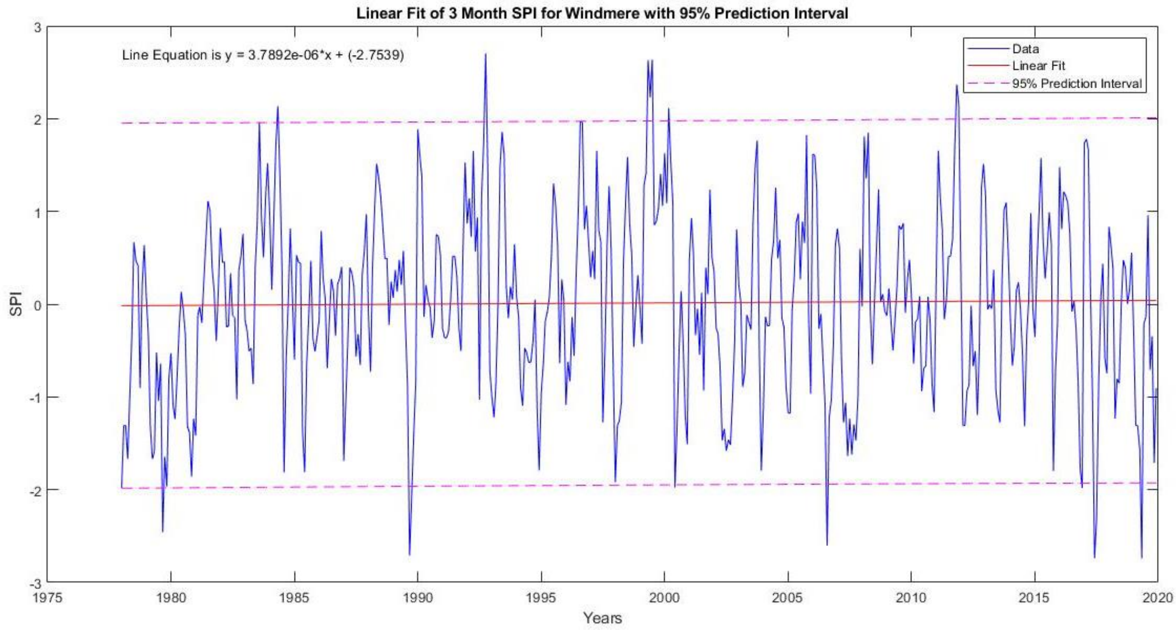

Figure 35: Regression Analysis of SPI at Windmere

5.5.2 Decadal Analysis

Analysis of decadal statistics (Table 13-14) suggests an increase in both frequency and duration of drought by deciles for Windmere, however 3-month SPI conflictingly suggest duration will be relatively unchanged. Severity by these methods also appears to be on the uptick. Although given the limited timeframe reviewed here and the poor linear relationship it is difficult to confirm these results with any statistical confidence (as seen in Table 15 regarding Figure 36 and Figure 37). Given the near decadal cyclic nature found in previous studies, it is possible that an alternating trend would be evident in these characteristics over a longer analysis.

Table 13: Monthly Decile Decadal Statistics

Windmere	2019-2010	2009-2000	1999-1990	1989-1980
Frequency of drought	20	24	16	18
Number of months ≤ 2.0 during growing period	11	14	6	9
Number of months ≤ 2.0	35	32	23	25
Average drought duration (months)	2.050	1.583	1.625	1.611
Average drought severity (DI)	1.642	1.340	1.328	1.481
Mean (DI)	5.150	5.242	5.842	5.567

Carnamah				
Frequency of drought	18	15	17	17
Number of months ≤ 2.0 during growing period	16	13	7	11
Number of months ≤ 2.0	33	19	24	23
Average drought duration (months)	2.389	1.800	1.588	1.588
Average drought severity (DI)	1.781	1.400	1.529	1.422
Mean (DI)	4.683	5.000	5.633	5.433

[1]Duration of drought assumed decile ≤ 2 until return to decile 5

Table 14: 3-month SPI Decadal Statistics

Windmere	2019-2010	2009-2000	1999-1990	1989-1980
Frequency of drought	10	8	6	6
Number of months ≤ -1.0 during growing period	7	15	2	6
Number of months ≤ -1.0	18	27	12	16
Average drought duration (months)	3.400	4.714	4.143	5.375
Average drought severity (SPI)	-1.201	-1.147	-0.827	-1.159
Mean (SPI)	-0.052	-0.048	0.319	0.001

Carnamah				
Frequency of drought	11	9	7	6
Number of months ≤ -1.0 during growing period	1	11	4	5
Number of months ≤ -1.0	29	23	17	14
Average drought duration (months)	3.455	5.000	3.857	5.500
Average drought severity (SPI)	-1.784	-1.004	-1.050	-1.033
Mean (SPI)	-0.301	-0.214	1.156	-0.056

Table 15: Regression Analysis of Drought Duration

Windmere	DoF	*p* each coefficient [*b c*]	R^2	R^2 Adjusted	RMSE
3-Month SPI Duration	25	[0.9618 0.9952]	9.3601e-05	-0.0399	1.7458
Month Deciles Duration[1]	74	[0.1486 0.1769]	0.0280	0.0148	0.7576
[1]Assuming drought duration Decile < 2 until returning to Decile 5					

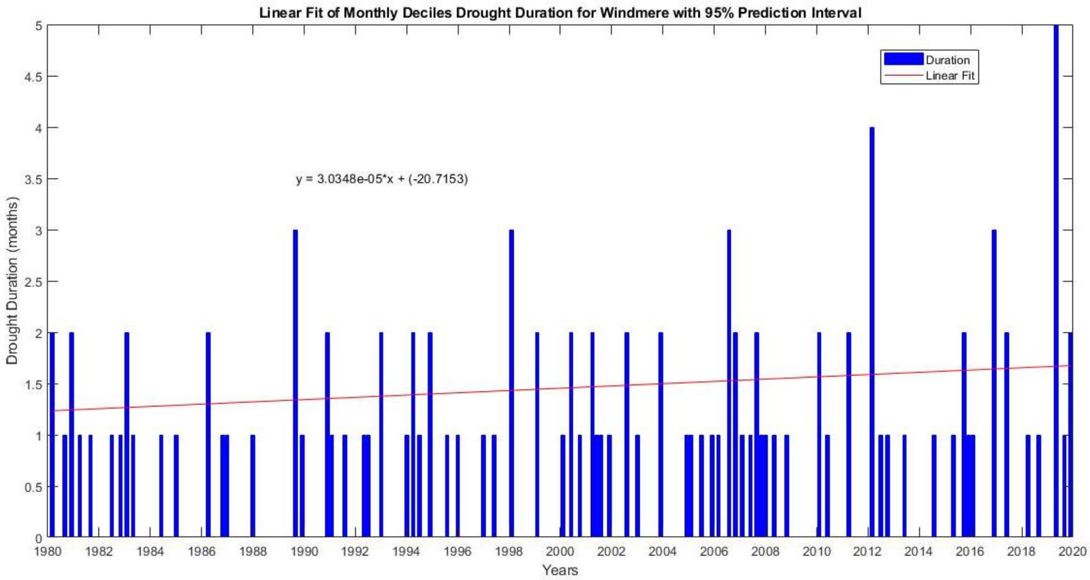

Figure 36: Monthly Deciles Drought Duration

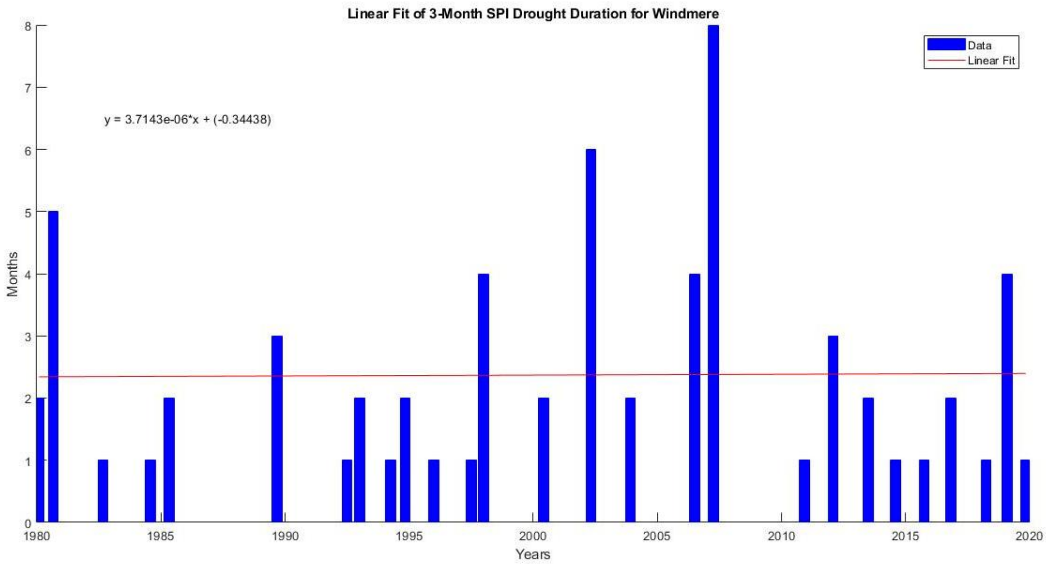

Figure 37: 3-Month SPI Drought Duration

5.5.3 Exploration of Long Short-Term Memory (LSTM)

Despite an exploration of LSTM for 3-month SPI at Windmere resulting in a larger RMSE that that of the linear regression, 1.1204 and 0.9784 respectively, LSTM appears to predict the variability well. The error is likely in its ability to model the severity with the predicted values regularly overestimated during training (Figure 38). Consequently, the value in this trend is the exposure of an underlying near decadal cyclic nature as suggested by previous research seen in Figure 39.

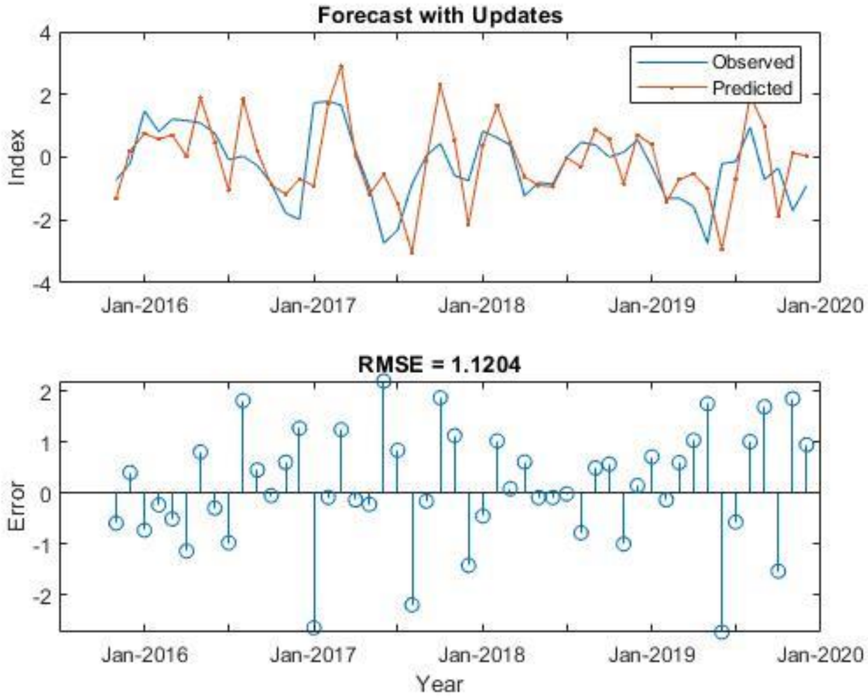

Figure 38: LSTM Forecast Training Period (Updated Index & Error)

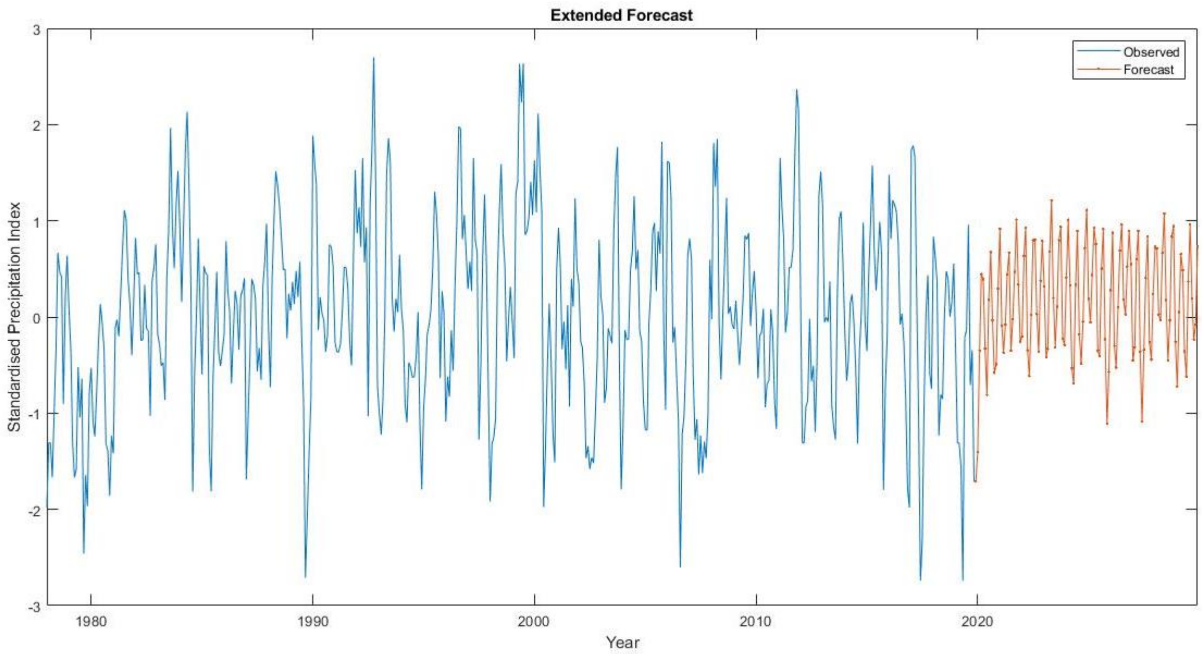

Figure 39: LSTM Forecast for 3-month SPI at Windmere

6. DISCUSSION

Despite the potential for rainfall within pockets of the study area to remain relatively unchanged the likely trend of increased temperatures ensures the area will be more prone to drought. Indices based purely on rainfall data lack consideration of soil moisture availability, however the ability to effectively estimate meteorologically based evapotranspiration inputs is constrained by limited available data (temperature, solar radiation, and humidity) and knowledge of crop water demand. Although it will take some time to develop a reliable historical context to improve drought indices, increased BoM station and radar coverage in recent years, with the installation of the Watheroo radar to the south of the study region and increased capabilities to observe Indian Ocean temperatures for example, will inevitably improve the available dataset.

Using an arbitrary three consecutive months to detect the onset of a significant rainfall deficiency does not appear to consistently characterise drought in the North Midlands region, which relies on May to September growing period rainfalls. In the past emerging drought conditions have been overlooked by failing to pinpoint the specific residence time of reference. In this context growing period deciles may be a more reliable method of characterising drought, however the ability to define the duration of drought makes SPI relevant. As such the definition of drought needs to be tailored to the chosen index with respect to the regional context.

Adapting the methods for deriving drought indices specifically for dryland farming regions is evidently vital. Suggestions have been made in the past that an alternative distribution, for example log normal distribution, more accurately models low rainfall SPI calculations and should be investigated with regards to the North Midlands. There is also an opportunity to further refine the residence period of both SPI and SPEI to the corresponding long-term record of growing period rainfall rather than all rainfall given the summer currently has limited bearing on crop viability in this region. This will capture the financial burden of successive drought years, despite each season having limited influence on the next in the context of drought onset.

Advances in agronomics and wheat genetics, particularly since the 1980's, has safeguarded Western Australian wheat yields despite a warming and drying climate (Heard 2019). Recent work by the Australian Grain Research and Development Corporation to produce varieties with an increased coleoptile length enabling wheat to be sown into sub-soil moisture from summer rain will surely provide grain growers with increased opportunities. However, with 25% of the seasons on record at Windmere failing to register a breaking rain prior to June and limited frost risk, it is likely the Northern Agricultural region is more suited to high yielding, drought tolerant cultivars. This will potentially come in the form of short season and heat tolerant varieties despite the focus country-wide historically being on long season varieties. Greater confidence in drought forecasts will provide much needed consensus in the direction of research and development.

In the past dryland farmers have sought the efficiency of economies of scale by acquiring more land. This is a tendency that ensues today, encouraged simply by an aging workforce exiting surrounding businesses, the lack of new farming enterprise due to significant entry restraints and current exemptions for land ownership in superannuation holdings. This expansion tends to be in one agro-ecological region due to the limitations of shifting large machinery and stock. Unfortunately, this greatly exposes farmers to the impact of climate change and in the event of mismanagement, it heightens the risk to community and the environment supported by those larger farmers. Schemes designed to alleviate drought impact in regional areas need to encourage the diversification of agricultural products and markets, and other risk reduction measures with due consideration of unintentional consequences.

7. FRAMEWORK

According to Australia's 2018 National Drought Agreement each of the states are responsible, amongst other shared roles, for the delivery of capability-building programs in preparation for drought, and land management and animal welfare during periods of drought. Although little has changed in this regard from the superseded 1992 policy, a strategy that is best suited to the diverse West Australian circumstances is still needed, particularly during the current period of reform. It is not necessary to rewrite or commit to resources provided by other states, however a drought management framework developed with input from local industry, like that produced for the State of Queensland (Figure 40), is required to ensure the capability to detect drought across all agricultural regions in Western Australia and in turn direct research and development (R&D) programs. Unfortunately, the Department of Primary Industries and Regional Development (DPIRD) in Western Australia appears to be falling behind in this obligation.

Figure 40: Drought Management Framework courtesy of Queensland Government (2019)

Despite a history of being overlooked for national drought funding, receiving only 2.23% of all payments for the Exceptional Circumstances Interest Rate Subsidy scheme in the decade to 2011, WA is arguably well positioned to set the benchmark for drought programs encouraging self-reliance (DoA&F 2014). The Federal Agriculture Minister David Littleproud, however, is critical of the progress achieved in the state (Brammer 2020). It is clear to see why this is the case, given Queensland Government's Long Paddock initiative which provides the widely used SILO database and numerous drought tools, and the development of a combined drought indicator in New South Wales. Western Australia, by its own omission, has no drought declaration system. Evidently, Western Australia has been constrained in its implementation of climate and weather tools to support real time decision making and direct R&D more effectively.

This may be a result of prioritisation given that BoM already provides this service, however it is impractical for drought indices relevant to WA regions to be developed at a national level; a lesson which should have been learnt by past examples of drought policy failing to adopt criteria appropriate to WA's cropping cycle. The federal government has worked to improve 'regional and local predictive and real-time drought indicator information' in recent years (*Drought in Australia: Australian Government Drought Response, Resilience and Preparedness Plan* 2019, p. 3). However, despite improved functionality and coverage of its own resources the DPIRD is yet to close the loop by developing a comprehensive drought declaration tool, crucial for business decision making and early warning capabilities.

Such a tool should incorporate all relevant meteorological observations: air temperature, humidity, rainfall, solar radiation, wind speed and direction, and carbon dioxide concentrations, thought to account for the water effectiveness. Thus, mitigating the risk of both rainfall and temperature induced drought and inevitability making it applicable to all regions of WA. This would require further development of crop coefficients, specific to those varieties and conditions in WA including soil-water behaviour. Evidently any drought strategies and tools will require continual review to maintain relevance with the evolving climatic scenario.

Past drought strategies have introduced tax management schemes, such as Farm Management Deposits, subsidies for water infrastructure, and numerous community programs, however as the impact of climate change develops more innovative on-farm strategies will be needed to maintain viability. In dryland farming regions, for example, there is a significant opportunity for summer diversification when combined with on-farm desalination or shifting focus to value-adding processes. Advances in research into the carbon dioxide fertiliser effect on wheat yield, adapting cultivars to thrive in the changing conditions and assessing the crop water availability via satellite remote sensing are all influencing the outlook of the industry. There is now a certain shift towards fostering drought resilience.

8. CONCLUSION

Although there is still a significant research gap between on-farm drought experiences and the ability to quantify drought in the study area this work begins to highlight the limitations in current estimation methods. There is evidently a lack in current data availability, a subsequent reliance on interpolated data for modelling, and poor development of tools for monitoring the influence of rainfall and temperature variability. Spatial analysis has shown that the climate trend is not consistent across the Northern Agricultural Region, let alone the entire Southern Land Division. Fundamentally, improvements are required to enable reliable probabilistic forecast of meteorological drought in the study region.

Industry preparedness for drought, and naturally the recovery, is dependent on the reliability of monitoring and early warning systems driving capability-building programs. The absence of framework specific to Western Australia jeopardises the state strategy for research and development that has been credited with bolstering wheat yields in the past. Rather than replicating work by other states Western Australia is well positioned to develop tools relevant to its significant dryland regions and differing climate drivers. This will likely involve the development of a combined drought index that broadens the ability of SPEI. There is, however, considerable work needed to get to that stage.

9. RECOMMENDATIONS

Potential further work in this area is limitless, however there are certain aspects that are crucial to defining reliable drought classification. As mentioned previously there is significant limitation in the current method for calculating potential crop evapotranspiration. This is firstly impeded by the station coverage of temperature, humidity, and solar radiation observations required to ensure accuracy in meteorologically derived evapotranspiration values. The digitisation of available farm-based records to safeguard existing historical data is a logical addition to this.

Secondly, the lack of research into the influence of crop growth on water demand in the Northern Agricultural Region of WA leaves the crop coefficient, K_c poorly estimated. A versatile study of the influence of physical and physiological factors on the evapotranspiration of different varieties of crops grown in the Northern Agricultural region is needed to improve these estimates. In this study consideration will need to be made regarding the varying influence of soil-water holding capacities in the region and the impact of changing climatic conditions including the carbon dioxide fertilisation effect that is likely with increased atmospheric concentrations. Alternatively, the development of a cost-effective on-farm (or via remotely satellite sensing) crop evapotranspiration tool may provide grain-growers with more reliable real time values for actual crop evapotranspiration.

Ultimately, the development of a combined drought indicator, like that produced by the NSW Department of Primary Industries which integrates a range of regionally relevant indices is required to provide improved drought classification. Given the continued need for statistically derived indicators, the foundation of this tool would require probability distributions that best model the regions rainfall and other climatic characteristics. Probabilistic forecasts based on such an indicator would also need to progress from weak linear regression models, possibly in the machine learning space.

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A1. Project Specification

ENG4111/4112 Research Project
Project Specification

For:	Jessica Mendonca
Title:	Characteristics and Modelling of Drought
Major:	Civil Engineering
Supervisors:	Rezaul Chowdhury
Enrolment:	ENG4111 – EXT S1, 2020
	ENG4112 – EXT S2, 2020
Project Aim:	To define and model meteorological drought in the Northern Agricultural region of Western Australia

Programme: Version 1, 21st February 2020

8. Define the characteristics of meteorological drought
9. Define indices relevant to meteorological drought in WA
10. Literature review with particular reference to the consequence of shifting climatic zones in Northern Agricultural Region of WA
11. Conduct spatial and temporal analysis of meteorological drought in Northern Agricultural Region WA specifically for the winter growing period using rainfall data from both BoM and other sources not previously digitised
12. Quantify likelihood of future meteorological drought for Northern Agricultural Region of WA based on 4.

If time and resources permit:

13. Conduct spatial and temporal analysis of meteorological drought in Northern Agricultural Region WA using rainfall and temperature

14. Develop a drought management strategy applicable to farmers in the Northern Agricultural Region WA

A2. Interview

40 Years of Farming Windmere
Transcribed: 14th May 2020
I = Interviewer, Jessica Mendonca
P1 = Participant 1, Jan Waite
P2 = Participant 2, Greg Waite
Time stamp: **[00:00:00]** - **[12:03:43]**

[00:00:00]	**I**	I know it is a busy time of year, thank you for taking the time to answer a few questions for my research. Firstly, what do you feel are the most important climate drivers impacting Windmere and how do you feel they have changed over the past 40 years?
[00:20:70]	**P1**	Being in the northern agricultural area 150 km from the coast our rainfall at Windmere isn't able to purely rely on the frontal systems. Frontal systems move from the south-west to the north-east losing rainfall intensity as they move further from the point of landfall. This reduces the amount of rain that is delivered in showers on the front to Windmere. No two years have been the same weather-wise in the last 40 years. And in all that time I only remember two years where we have not looked for rain but have had it fall on a consistent basis as needed… like watering a garden. And one of those was light on total annual growing season rainfall but a good year production wise. Years when patterns of the frontal band consistently peak before reaching the coast and then slide to the south happen causing reduced rainfall in the northern agricultural. We sometimes feel that the coast is toxic to rain causing drought conditions. A reaction of the frontal band with a cloudband, particularly mid-level cloud dragged down into the front ensures more rainfall. We are more dependent on rain moving in from the north-west than further south in the wheatbelt. Formation of cut-off lows and mid-level lows provide us with good rains. Our knowledge of local weather patterns drivers has increased along with access to the internet, multiple modelling programs predicting weather and increased BoM knowledge. But when looking at past events and interpreting current climate we don't know if what we are seeing has changed or whether it was always happening but we didn't know about it when looking at a fuzzy satellite picture on the ABC News Weather. Our weather patterns vary over longer almost decade periods. The drivers vary… sometimes one such as Indian Ocean TEMPs, or the position of where the fronts peak as they approach the coast seem to have more affects, other times the presence of the north-west cloudband moving further south is more reactive. I don't feel that the BoM has found all the drivers yet because this toxic coast affect is never explained. On occasion it will not rain despite modelling saying it should and other times we get good solid rains totally unforecast by BoM.

		Windmere's rainfall does not appeared to have changed much in amount on average over the last 40 years. Cut-off lows split from the rest of the front and coming over the Midwest coast seem to be more common in this century, giving us rain despite the showers of the front losing their intensity over the wheatbelt. This has sometimes given us more rain than the South-west, from the same system.
[03:41:34]	**I**	Now AGRIC are projecting decreasing rainfalls and increasing temperatures for the North Eastern Agricultural region which encompasses your farm, what do you make of this?
[03:50:51]	**P1**	I don't agree with their predictions. Yes, I think there's going to be increasing temperatures and I think they need to get their act together and help breed us some wheats which are more resistant to heat stress. Heat stress is becoming our biggest issue. It's a lot more damaging to us than frost. In our area heat stress is the big concern, not frost. There are some varieties like Wyalkatchem which I think actually have some traits which can handle it but in general the wheats we are using bomb out. So heat stress means they abort flowering, and abort-- that's the end of it. And they abort grain and potentially stress our grain, so it looks a bit like frost damage but actually it's heat stress. It pinches the grain off. So that's temperature….The rainfall, did they say variability or deficiency?
[04:44:55]	**I**	They said decreasing.
[04:46:64]	**P1**	Decreasing, I actually don't believe our rainfall is decreasing. If you look at our rainfall charts, I think our rainfall is much the same as it was. Any decrease has been minimal. It's increasing in variability in that we have had-- our rainfall seems to go in decade periods of time. In the 90's it seemed more reliable, in the 00's it seemed to be more droughts. In all the years we've had three proper droughts… solid droughts… out of seven lesser years and the other years were good. [silence] The teen decade that improved… we still had droughts, but we had good years as well. We had exceptional years. But '03 I think might have been an exceptional year too. We've had good years in that decade too but there's been more droughts. Now in this decade… it seems to be ok but we are having dry years and… it's variable… it's just variable. It's harder to predict.
[05:53:20]	**I**	So in the 00's you'd say you had more low years, that didn't necessarily record as a drought?
[06:00:27]	**P1**	No, in the 00's the worst drought… and I think they're worse than the ones we've had since, Greg may not agree. We've had a bad drought in… '02. But '03 was a good year. If I remember. I haven't got the charts in front of me so I'm going on memory. But I think the next year was a good year.
[06:25:00]	**I**	I was working on the receival bins in Mingenew '03 and it was a fantastic year for Mingenew. It broke records.
[06:34:57]	**P1**	Whereas the year before was a drought and we went "Whoa". And that's when I painted the house blue. I didn't mentally cope with it very well as we hadn't had a drought. The last drought, when we would have said, "This is a drought!" was in the 70's. It was those ones like… '79 and '77 we had droughts.

		The 80's were dry. The 80's were a bit like what we dealt with last decade. The 80's were dry but there weren't droughts. And basically, my gut feeling of the 80's… was that each year was a little bit better, then the alternate year was a little bit worse but not as bad as the last … steadily increasing. And I think that was rainfall, but it also would have been that we were improving our farming practices at the same time. Wheat varieties, no till came in, better use of fertilisers, better chemicals… we started spraying. Prior to the 80's we didn't use a boom spray on the farm so then meant we could now sow earlier… we didn't have to work up, work back… we didn't have to dry out the ground. There was a major shift in farming practices in the 80's. So '02 came along and it just pulled the rug out from under my feet and mentally I didn't cope very well. We had not had a drought for a while. 80's we like that, we were trying to build up the farm, we were young and broke. 90's things were a lot easier and the weather was a lot easier to deal with and it worked a lot better. We didn't have any drought in the 90's. Then '02 came along. And we thought it shouldn't have hit us as bad as the droughts in the 70's. It was not to be unexpected, but we'd had a good period of about 20 years. Then '03 came along and it was a really good year again. And we picked ourselves up again and said, "Well we've had our drought". '06 came along and … '06 wasn't so bad. It was worse than '02 but it wasn't so bad mentally. But '07 came along and it was worse than '06. And in my mind worse than any drought in our farming history, so at that time 30 years… it didn't rain and coming on top of having a drought the previous year, that's two years of economic kick in the gut. [silence] So things improved again but not… we've had some good years… you see I think 2010 and again you'll have to check, I think it was ok for us but for Western Australia it was considered a drought. Because what seems to happen with droughts is we have… I don't know if this is scientifically correct. But it feels like we have a drought or dry year here, at Windmere, and then the following year Wyalkatchem tends to get them. The following year is heads further south again. And then maybe the following year Albany and Esperance-Franklin area might get a drought, then it disappears out of the state. It just feels that way, but I don't know if that's true.
[10:00:00]	**I**	In the past you have said the growing period is more likely May to September at Windmere, what leads you to believe this?
[10:09:97]	**P1**	Although we may receive some rainfall in April, any time before about the 25th of April can't generally be taken as part of the growing season as if germination occurs then crops are usually subjected to an extended hot dry period before the real break which stressed the plants detrimentally, reducing vigour, if not killing outright. The crops don't usually recover enough to yield as much or more than crops germinating three weeks later that have more chance of receiving rain when needed. An exception can be if a lot of subsoil moisture is available but even then temperatures and humidity in April are often not suitable for temperate

		crops… as indicated by the fact that during early rainfall winter growing weeds don't germinate until there is a change in the weather. At the other end of the growing period, the canopy of crop with its high-water requirement has to deal with increasing temperatures and evaporation. Our crops are generally mature by mid-October and we may be harvesting by the last week of October. Rainfall in late September is often too late to benefit crops sown in early May… which is our preferred sowing time given rainfall. A hot dry period often precedes rainfall in September, finishing the crop before finishing rains. Which is particularly detrimental to crops sown any later than the first week in June in a lot of seasons.
[11:51:61]		[sound cut]
[11:53:54]	**I**	Which years would you consider drought years?
[11:56:51]	**P2**	What do you define as drought?
[11:59:00]	**I**	Based on crop failing or withholding planned crops.
[12:03:43]	**P2**	1977, 1979 when I first came home, again 1994 was a poor year, then 2002, 2006 and 2007… 2017, and 2019 wasn't great either. Press wells and furrow sowing has changed everything. We used to plough before we sow, and this obviously would dry it out. When you compare the combine to the bar that we have now is chalk and cheese. We're able to seed earlier and quicker. So 2019 was not really a drought but if you transplanted into the 70s, compared to the amount of rainfall it would be just as bad. We're just growing a lot more wheat for the millimetres that we get. As a guide we need 125mm to harvest, and every inch above that is about a bag to the acre. If we can get rain in May, just enough to get it in and get it established, we'll be fine. It's like 2018 we didn't get much but it just kept coming and we grew a very good crop.

A3. Windmere Monthly Rainfall Record

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Grand Total
1977	0	0	0	40.5	20	25.25	12.5	38.5	0	0	0	0	136.75
1978	0	0	0	0	30.25	54.25	85.25	12.5	28	10	8.25	22.5	251
1979	0	0	0	0	17	60	14.25	34.5	2.25	0	11	3.25	142.25
1980	2.5	0	0	17.25	39.5	49.5	43.25	27	5	9.25	0	0	193.25
1981	4.75	24.5	9	0.5	72	64.5	59.25	53	12.75	9.5	12	8.25	330
1982	36	5.5	19.75	7.25	30.75	78.5	20.25	28.25	34	19.5	0	24.25	304
1983	0	0	21.25	4	9.25	107.25	65.75	53.75	25	7	38.75	20.5	352 5
1984	2.5	15.5	70	61.25	105.5	12.75	35.75	24.5	34.5	13.25	13 5	2	391
1985	0	51.25	9.75	0	11.5	25	70	33	24.5	5	2.75	13	245.75
1986	8.5	43.75	0	0	40	52	56.75	29.5	15.25	32.75	0	2.5	281
1987	0	4.75	19.25	34.75	33	41	36	43.25	13.25	23.75	18	7.75	274.75
1988	0	5.5	52	36.75	85.75	57	55.75	55.75	16.75	13	7.75	11	397
1989	11.75	23.75	9.75	29.5	40.5	59.75	25.5	15.5	5.5	9	4.75	0	235.25
1990	106	5.5	11.25	19.5	49	33.25	51.25	34.25	21	38	0	0	369
1991	22.25	0	3.5	27.5	39.75	59.25	62.5	23.25	18.25	17.75	20	28.75	322.75
1992	9.5	45.5	21.5	74.5	5.25	71.5	15	97.75	63.75	6.25	9.25	0	419.75
1993	0	3	8.5	29.75	133.5	53.25	40.75	46.5	20	10.25	12.75	18	376.25
1994	0	10.5	0	0	48	28.75	30.5	50.25	19	3.75	0	0	190.75
1995	10	5.25	17	16	39.75	71.25	96.5	12.25	24.5	19.5	3.75	4.5	320.25
1996	0	11.25	1	24	19.75	72.5	95.75	59.25	31	4.75	32.25	4.75	356.25
1997	0	50.5	1	90.25	25.5	19.5	38	57	38.5	15	0.75	0	336
1998	0	0	2	9.25	81.75	69.5	75	25.75	28.75	5.75	7	20.5	325.25
1999	0	0	114.75	7.5	173	66.5	64.25	38.75	39.75	23.75	14.75	13.5	556 5
2000	67.25	0	123.75	8	7	17.75	55.5	40	21	0	0.75	5.75	346.75
2001	37	29.5	0	0	66.5	9.5	65.25	24.25	35.5	14.75	22.75	0	305
2002	16.25	9	2	8.25	9	31.5	32.5	18.75	19.25	10.25	4.25	30.5	191 5
2003	0	3.25	7.5	7.5	48.25	35	39.25	97	29.25	2.25	1 5	0	270.75
2004	6.25	22.5	1.5	9	85.5	41.5	77.75	34	23.75	10	3.25	0	315
2005	4	0	32.5	20.75	69.25	64	15.25	92	27	11.75	0 5	0	337
2006	94.5	17.75	0	14	49.75	9.75	30.25	14.25	33.25	0.25	0	40.5	304.25
2007	15.5	0	3.25	4	21.5	15.25	47.75	15.25	12.75	11.75	0	28	175
2008	0	98.75	22	38	5.75	28.25	101.75	28.25	26	18.25	0	7.25	374.25
2009	18.25	13.5	1.5	9.5	49.5	51	79.5	36.75	25.75	6.75	15	15.25	322.25
2010	0	0	31.75	3.75	37.75	20	47	41	26.5	0	0	10	217.75
2011	26.75	79.25	0	1.75	59.25	41	61.25	52	22.5	49.75	39.75	0	433.25
2012	0	0	0	13.75	20.5	64.75	20.5	28.25	29.5	2.75	41 5	21.75	243.25
2013	8	1.5	29.75	8.25	51	3	33.75	51.5	34.75	15.5	18.75	5	260.75
2014	1.5	8.25	13	26	42.25	28.75	40	18.25	43.25	11.25	11.25	3.5	247.25
2015	5.5	40.75	44.75	49.75	15.75	48	101.5	26.5	5.5	2.25	21	0	361.25
2016	66.25	0	43.5	60.75	34.5	45.25	51.75	37	15	0	0	0	354
2017	101.75	23	22.25	4	5	10	37.25	54.25	22	7.5	1 5	6	294 5
2018	49.25	2	6	0	30.25	34.25	70.5	47.75	6.5	17.5	21.25	0	285.25
2019	0	0	0	2.5	1.5	86.25	41	47.25	2.75	13	0	0	194.25

A4. MATLAB Code Written by Jessica Mendonca

Table of Contents

Deciles

Deciles.m finds station files in directory, preprocesses the data to account for missing data and incomplete periods before deciles are calculated. Plots and output for use in ArcGIS® is then saved to file.

Contents

Find Files in Directory

```
clear all

fds = fileDatastore('C:\Users\Jessica\Desktop\Uni QLD\2020\Drought Thesis\Data\BOM Downloa
ds\*\*Data1.csv', 'ReadFcn', @importdata)
fullFileNames = fds.Files
numFiles = length(fullFileNames)
output = timetable();
monthly_output = timetable();
```

Loop Over All Station Files

```
for k = 1 : numFiles
```

```
    pathparts = strsplit(fullFileNames{k},filesep);
    station = string(pathparts(10));
    fprintf('Now reading file %s\n',station);
```

Specify Station Coordinates

```
    if      station == 'Windmere'
```

```
            coordinates = table(-29.8514, 116.2863,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Warradarge'
            coordinates = table(-30.0722, 115.3136,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Leeman'
            coordinates = table(-29.9486, 114.9781,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Coorow'
            coordinates = table(-29.8814, 116.0229,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Minaru'
            coordinates = table(-29.8497, 116.2289,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Koobabie'
            coordinates = table(-29.9414, 116.2003,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Hakea'
            coordinates = table(-30.0989, 116.2339,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Ytiniche'
            coordinates = table(-30.0706, 116.2092,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Latham'
            coordinates = table(-29.7586, 116.4444,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Perenjori'
            coordinates = table(-29.4417, 116.2875,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Perangery'
            coordinates = table(-29.3692, 116.4061,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Wanarra'
            coordinates = table(-29.5147, 116.8011,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Oaklands'
            coordinates = table(-29.4667, 116.1325,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Five Gums'
            coordinates = table(-29.4847, 116.0703,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Eneabba'
            coordinates = table(-29.8183, 115.2722,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Twin Hills'
            coordinates = table(-29.6708, 115.3636,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Carnamah'
            coordinates = table(-29.6886, 115.8872,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Highfields'
            coordinates = table(-29.6006, 115.9392,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Green Grove'
            coordinates = table(-29.5486, 115.0689,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Irwin House'
            coordinates = table(-29.2236, 115.1075,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Dongara'
            coordinates = table(-29.2528, 114.9306,'VariableNames',{'Latitude', 'Longi
```

```
tude'});
    elseif   station == 'Mindarra'
                coordinates = table(-29.0636, 115.1753,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Three Springs'
                coordinates = table(-29.5339, 115.7628,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Fairfield'
                coordinates = table(-29.4714, 115.8528,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Mingenew'
                coordinates = table(-29.1906, 115.4414,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Yandanooka'
                coordinates = table(-29.2872, 115.6331,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Arena'
                coordinates = table(-29.3586, 115.4503,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Yarragadee'
                coordinates = table(-29.0767, 115.4092,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Manarra'
                coordinates = table(-29.0711, 115.6261,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'South Holmwood'
                coordinates = table(-29.0364, 115.5536,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Strawberry North'
                coordinates = table(-29.1514, 115.2428,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Morowa'
                coordinates = table(-29.2103, 116.0089,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Canna'
                coordinates = table(-28.8975, 115.8627,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Pindawa'
                coordinates = table(-28.8956, 115.8106,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Mallee Vale'
                coordinates = table(-29.2419, 115.7794,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Nindethana Farm'
                coordinates = table(-28.8114, 115.9675,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Mellenbye'
                coordinates = table(-28.8883, 116.1947,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Yongarloo'
                coordinates = table(-29.1858, 115.7406,'VariableNames',{'Latitude', 'Longi
tude'});

    end
```

Format Data and Compile Timetable

```
    Tbl = readtable(fullFileNames{k},'Format','%s %s %s %s %f %s');
    Rainfall = table2array(Tbl(:,5));
    y = Tbl.Year;
```

```
    m = Tbl.Month;
    m_y = strcat(m, {'-'}, y);
    t = datetime(m_y,'InputFormat','MM-yyyy','Format','MMM-yyyy');
    Dataseries = table2timetable((Tbl(:,5)),'RowTimes',t);
```

Filter Incomplete Years

```
    filter = [];
    count = [groupcounts(Dataseries.Time,'year')];

    for i = 1:length(count)
        for j = 1:count(i,1)
            logic = [groupcounts(Dataseries.Time,'year')==12];
            filter =[filter; logic(i,1)];
        end
    end

    FilteredDataseries = Dataseries(logical(filter),:);
```

Compile Annual & Quarterly Timeseries

```
    Q_Rainfall = retime(FilteredDataseries,'regular','Timestep',calquarters(1));
    Qu_Rainfall = retime(FilteredDataseries,'quarterly','sum');
    Quarterly_Rainfall = [];

    for w = 1:size(Qu_Rainfall)
        if  isnan(Q_Rainfall.MonthlyPrecipitationTotal_millimetres_(w,1)) == 1
            Quarterly_Rainfall = [Quarterly_Rainfall; {NaN}]; % Missing data filled with N
aNs
        else
            Quarterly_Rainfall = [Quarterly_Rainfall; Qu_Rainfall(w,1)];
        end
    end

    A_Rainfall = retime(FilteredDataseries,'regular','Timestep',calyears(1));
    An_Rainfall = retime(FilteredDataseries,'yearly','sum');
    Annual_Rainfall = [];

    for x = 1:size(An_Rainfall)
        if  isnan(A_Rainfall.MonthlyPrecipitationTotal_millimetres_(x,1)) == 1
            Annual_Rainfall = [Annual_Rainfall; {NaN}]; % Missing data filled with NaNs
        else
            Annual_Rainfall = [Annual_Rainfall; An_Rainfall(x,1)];
        end
    end
```

Compile Growing Period Timeseries

```
    for r=1:height(Tbl)
        precip = Tbl(ismember(m,{'05' '06' '07' '08' '09' '5' '6' '7' '8' '9'}),3:5);
    end

    yr = precip.Year;
    mnth = precip.Month;
    m_y = strcat(mnth, {'-'}, yr);
    t = datetime(m_y,'InputFormat','MM-yyyy','Format','MMM-yyyy');
```

```
GrowingPeriod_Dataseries = table2timetable((precip(:,3)),'Rowtimes',t);
```

Filter Incomplete Growing Periods

```
filter = [];
count = [groupcounts(GrowingPeriod_Dataseries.Time,'year')];

for s = 1:length(count)
    for t = 1:count(s,1)
        logic = [groupcounts(GrowingPeriod_Dataseries.Time,'year')==5];
        filter =[filter; logic(s,1)];
    end
end

GrowingPeriod_FilteredDataseries = GrowingPeriod_Dataseries(logical(filter),:);

G_Rainfall = retime(GrowingPeriod_FilteredDataseries,'regular','Timestep',calyears(1))
;
Gr_Rainfall = retime(GrowingPeriod_FilteredDataseries,'yearly','sum');

GrowingPeriod_Rainfall = [];

for z = 1:size(Gr_Rainfall)
    if  isnan(G_Rainfall.MonthlyPrecipitationTotal_millimetres_(z,1)) == 1
        GrowingPeriod_Rainfall = [GrowingPeriod_Rainfall; {NaN}]; % Missing data fille
d with NaNs
    else
        GrowingPeriod_Rainfall = [GrowingPeriod_Rainfall; Gr_Rainfall(z,1)];
    end
end
```

Compile Winter Timeseries

```
for u=1:height(Tbl)
    precip = Tbl(ismember(m,{'06' '07' '08' '6' '7' '8'}),3:5);
end

ye = precip.Year;
mo = precip.Month;
m_y = strcat(mo, {'-'}, ye);
t = datetime(m_y,'InputFormat','MM-yyyy','Format','MMM-yyyy');

Winter_Dataseries = table2timetable((precip(:,3)),'Rowtimes',t);
```

Filter Incomplete Winter Periods

```
filter = [];
count = [groupcounts(Winter_Dataseries.Time,'year')];
for v = 1:length(count)
    for w = 1:count(v,1)
        logic = [groupcounts(Winter_Dataseries.Time,'year')==3];
        filter =[filter; logic(v,1)];
    end
end

Winter_FilteredDataseries = Winter_Dataseries(logical(filter),:);
W_Rainfall = retime(Winter_FilteredDataseries,'regular','Timestep',calyears(1));
```

```
    Wi_Rainfall = retime(Winter_FilteredDataseries,'yearly','sum');
    Winter_Rainfall = [];

    for y = 1:size(An_Rainfall)
        if  isnan(W_Rainfall.MonthlyPrecipitationTotal_millimetres_(y,1)) == 1
            Winter_Rainfall = [Winter_Rainfall; {NaN}]; % Missing data filled with NaNs
        else
            Winter_Rainfall = [Winter_Rainfall; Wi_Rainfall(y,1)];
        end
    end
```

Process Decile Bands

```
    Quarterly_DI = prctile((Quarterly_Rainfall.MonthlyPrecipitationTotal_millimetres_),[10
 20 30 40 50 60 70 80 90 100]);
    Annual_DI = prctile((Annual_Rainfall.MonthlyPrecipitationTotal_millimetres_),[10 20 30
 40 50 60 70 80 90 100]);
    GrowingPeriod_DI = prctile((GrowingPeriod_Rainfall.MonthlyPrecipitationTotal_millimetr
es_),[10 20 30 40 50 60 70 80 90 100]);
    Winter_DI = prctile((Winter_Rainfall.MonthlyPrecipitationTotal_millimetres_),[10 20 30
 40 50 60 70 80 90 100]);
    Doze = [10:10:100].';

    DI = table(Doze,[Annual_DI.'],[Quarterly_DI.'],[GrowingPeriod_DI.'],[Winter_DI.']);
    DI.Properties.VariableNames = {'Deciles','Annual','Quarterly','Growing Period','Winter
'};
```

Compile Growing Period Decile Timeseries for use in ArcGIS®

```
    values = GrowingPeriod_Rainfall.Variables;

    for i = 1:size(GrowingPeriod_Rainfall)
        if values(i,1) <= GrowingPeriod_DI(1,1)
            d = 1;
        elseif values(i,1) <= GrowingPeriod_DI(1,2)
            d = 2;
        elseif values(i,1) <= GrowingPeriod_DI(1,3)
            d = 3;
        elseif values(i,1) <= GrowingPeriod_DI(1,4)
            d = 4;
        elseif values(i,1) <= GrowingPeriod_DI(1,5)
            d = 5;
        elseif values(i,1) <= GrowingPeriod_DI(1,6)
            d = 6;
        elseif values(i,1) <= GrowingPeriod_DI(1,7)
            d = 7;
        elseif values(i,1) <= GrowingPeriod_DI(1,8)
            d = 8;
        elseif values(i,1) <= GrowingPeriod_DI(1,9)
            d = 9;
        elseif values(i,1) <= GrowingPeriod_DI(1,10)
            d = 10;
        end

        output = rmmissing([output; timetable(d, station, coordinates{1,1}, coordinates{1,
2}, 'RowTimes', GrowingPeriod_Rainfall.Time(i))]);

    end
```

Extract 2006 & 2007 Growing Period Deciles

```
    ZeroSix = timetable2table(output(((month(output.Time)== 1) & (year(output.Time)== 2006
)),:),'ConvertRowTimes',false);
    ZeroSeven = timetable2table(output(((month(output.Time)== 1) & (year(output.Time)== 20
07)),:),'ConvertRowTimes',false);
```

Compile Individual Month Decile Timeseries for use in ArcGIS®

```
    Jan = Dataseries((or(month(Dataseries.Time)== 1, month(Dataseries.Time)== 01)),:);
    Jan_DI = prctile((Jan.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Jvalues = Jan.Variables;
    Jan_output = timetable();

    for i = 1:size(Jan)
        if Jvalues(i) <= Jan_DI(1,1)
            d = 1;
        elseif Jvalues(i) <= Jan_DI(1,2)
            d = 2;
        elseif Jvalues(i) <= Jan_DI(1,3)
            d = 3;
        elseif Jvalues(i) <= Jan_DI(1,4)
            d = 4;
        elseif Jvalues(i) <= Jan_DI(1,5)
            d = 5;
        elseif Jvalues(i) <= Jan_DI(1,6)
            d = 6;
        elseif Jvalues(i) <= Jan_DI(1,7)
            d = 7;
        elseif Jvalues(i) <= Jan_DI(1,8)
            d = 8;
        elseif Jvalues(i) <= Jan_DI(1,9)
            d = 9;
        elseif Jvalues(i) <= Jan_DI(1,10)
            d = 10;
        end

        Jan_output = rmmissing([Jan_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Jan.Time(i))]);

    end

    Feb = Dataseries((or(month(Dataseries.Time)== 2, month(Dataseries.Time)== 02)),:);
    Feb_DI = prctile((Feb.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Fvalues = Feb.Variables;
    Feb_output = timetable();

    for i = 1:size(Feb)
        if Fvalues(i) <= Feb_DI(1,1)
            d = 1;
        elseif Fvalues(i) <= Feb_DI(1,2)
            d = 2;
        elseif Fvalues(i) <= Feb_DI(1,3)
            d = 3;
        elseif Fvalues(i) <= Feb_DI(1,4)
            d = 4;
```

```
        elseif Fvalues(i) <= Feb_DI(1,5)
            d = 5;
        elseif Fvalues(i) <= Feb_DI(1,6)
            d = 6;
        elseif Fvalues(i) <= Feb_DI(1,7)
            d = 7;
        elseif Fvalues(i) <= Feb_DI(1,8)
            d = 8;
        elseif Fvalues(i) <= Feb_DI(1,9)
            d = 9;
        elseif Fvalues(i) <= Feb_DI(1,10)
            d = 10;
        end

        Feb_output = rmmissing([Feb_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Feb.Time(i))]);

    end

    Mar = Dataseries((or(month(Dataseries.Time)== 3, month(Dataseries.Time)== 03)),:);
    Mar_DI = prctile((Mar.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Mvalues = Mar.Variables;
    Mar_output = timetable();

    for i = 1:size(Mar)
        if Mvalues(i) <= Mar_DI(1,1)
            d = 1;
        elseif Mvalues(i) <= Mar_DI(1,2)
            d = 2;
        elseif Mvalues(i) <= Mar_DI(1,3)
            d = 3;
        elseif Mvalues(i) <= Mar_DI(1,4)
            d = 4;
        elseif Mvalues(i) <= Mar_DI(1,5)
            d = 5;
        elseif Mvalues(i) <= Mar_DI(1,6)
            d = 6;
        elseif Mvalues(i) <= Mar_DI(1,7)
            d = 7;
        elseif Mvalues(i) <= Mar_DI(1,8)
            d = 8;
        elseif Mvalues(i) <= Mar_DI(1,9)
            d = 9;
        elseif Mvalues(i) <= Mar_DI(1,10)
            d = 10;
        end

        Mar_output = rmmissing([Mar_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Mar.Time(i))]);

    end

    Apr = Dataseries((or(month(Dataseries.Time)== 4, month(Dataseries.Time)== 04)),:);
    Apr_DI = prctile((Apr.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Avalues = Apr.Variables;
    Apr_output = timetable();

    for i = 1:size(Apr)
        if Avalues(i) <= Apr_DI(1,1)
```

```
            d = 1;
        elseif Avalues(i) <= Apr_DI(1,2)
            d = 2;
        elseif Avalues(i) <= Apr_DI(1,3)
            d = 3;
        elseif Avalues(i) <= Apr_DI(1,4)
            d = 4;
        elseif Avalues(i) <= Apr_DI(1,5)
            d = 5;
        elseif Avalues(i) <= Apr_DI(1,6)
            d = 6;
        elseif Avalues(i) <= Apr_DI(1,7)
            d = 7;
        elseif Avalues(i) <= Apr_DI(1,8)
            d = 8;
        elseif Avalues(i) <= Apr_DI(1,9)
            d = 9;
        elseif Avalues(i) <= Apr_DI(1,10)
            d = 10;
        end

        Apr_output = rmmissing([Apr_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Apr.Time(i))]);

    end

    May = Dataseries((or(month(Dataseries.Time)== 5, month(Dataseries.Time)== 05)),:);
    May_DI = prctile((May.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Mayvalues = May.Variables;
    May_output = timetable();

    for i = 1:size(May)
        if Mayvalues(i) <= May_DI(1,1)
            d = 1;
        elseif Mayvalues(i) <= May_DI(1,2)
            d = 2;
        elseif Mayvalues(i) <= May_DI(1,3)
            d = 3;
        elseif Mayvalues(i) <= May_DI(1,4)
            d = 4;
        elseif Mayvalues(i) <= May_DI(1,5)
            d = 5;
        elseif Mayvalues(i) <= May_DI(1,6)
            d = 6;
        elseif Mayvalues(i) <= May_DI(1,7)
            d = 7;
        elseif Mayvalues(i) <= May_DI(1,8)
            d = 8;
        elseif Mayvalues(i) <= May_DI(1,9)
            d = 9;
        elseif Mayvalues(i) <= May_DI(1,10)
            d = 10;
        end

        May_output = rmmissing([May_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', May.Time(i))]);

    end

    Jun = Dataseries((or(month(Dataseries.Time)== 6,month(Dataseries.Time)== 06)),:);
```

```
    Jun_DI = prctile((Jun.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Junvalues = Jun.Variables;
    Jun_output = timetable();

    for i = 1:size(Jun)
        if Junvalues(i) <= Jun_DI(1,1)
            d = 1;
        elseif Junvalues(i) <= Jun_DI(1,2)
            d = 2;
        elseif Junvalues(i) <= Jun_DI(1,3)
            d = 3;
        elseif Junvalues(i) <= Jun_DI(1,4)
            d = 4;
        elseif Junvalues(i) <= Jun_DI(1,5)
            d = 5;
        elseif Junvalues(i) <= Jun_DI(1,6)
            d = 6;
        elseif Junvalues(i) <= Jun_DI(1,7)
            d = 7;
        elseif Junvalues(i) <= Jun_DI(1,8)
            d = 8;
        elseif Junvalues(i) <= Jun_DI(1,9)
            d = 9;
        elseif Junvalues(i) <= Jun_DI(1,10)
            d = 10;
        end

        Jun_output = rmmissing([Jun_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Jun.Time(i))]);

    end

    Jul = Dataseries((or(month(Dataseries.Time)== 7, month(Dataseries.Time)== 07)),:);
    Jul_DI = prctile((Jul.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Julvalues = Jul.Variables;
    Jul_output = timetable();

    for i = 1:size(Jul)
        if Julvalues(i) <= Jul_DI(1,1)
            d = 1;
        elseif Julvalues(i) <= Jul_DI(1,2)
            d = 2;
        elseif Julvalues(i) <= Jul_DI(1,3)
            d = 3;
        elseif Julvalues(i) <= Jul_DI(1,4)
            d = 4;
        elseif Julvalues(i) <= Jul_DI(1,5)
            d = 5;
        elseif Julvalues(i) <= Jul_DI(1,6)
            d = 6;
        elseif Julvalues(i) <= Jul_DI(1,7)
            d = 7;
        elseif Julvalues(i) <= Jul_DI(1,8)
            d = 8;
        elseif Julvalues(i) <= Jul_DI(1,9)
            d = 9;
        elseif Julvalues(i) <= Jul_DI(1,10)
            d = 10;
        end
```

```
        Jul_output = rmmissing([Jul_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Jul.Time(i))]);

    end

    Aug = Dataseries((or(month(Dataseries.Time)== 8, month(Dataseries.Time)== 08)),:);
    Aug_DI = prctile((Aug.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Augvalues = Aug.Variables;
    Aug_output = timetable();

    for i = 1:size(Aug)
        if Augvalues(i) <= Aug_DI(1,1)
            d = 1;
        elseif Augvalues(i) <= Aug_DI(1,2)
            d = 2;
        elseif Augvalues(i) <= Aug_DI(1,3)
            d = 3;
        elseif Augvalues(i) <= Aug_DI(1,4)
            d = 4;
        elseif Augvalues(i) <= Aug_DI(1,5)
            d = 5;
        elseif Augvalues(i) <= Aug_DI(1,6)
            d = 6;
        elseif Augvalues(i) <= Aug_DI(1,7)
            d = 7;
        elseif Augvalues(i) <= Aug_DI(1,8)
            d = 8;
        elseif Augvalues(i) <= Aug_DI(1,9)
            d = 9;
        elseif Augvalues(i) <= Aug_DI(1,10)
            d = 10;
        end

        Aug_output = rmmissing([Aug_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Aug.Time(i))]);

    end

    Sep = Dataseries((or(month(Dataseries.Time)== 9, month(Dataseries.Time)== 09)),:);
    Sep_DI = prctile((Sep.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Svalues = Sep.Variables;
    Sep_output = timetable();

    for i = 1:size(Sep)
        if Svalues(i) <= Sep_DI(1,1)
            d = 1;
        elseif Svalues(i) <= Sep_DI(1,2)
            d = 2;
        elseif Svalues(i) <= Sep_DI(1,3)
            d = 3;
        elseif Svalues(i) <= Sep_DI(1,4)
            d = 4;
        elseif Svalues(i) <= Sep_DI(1,5)
            d = 5;
        elseif Svalues(i) <= Sep_DI(1,6)
            d = 6;
        elseif Svalues(i) <= Sep_DI(1,7)
            d = 7;
```

```
        elseif Svalues(i) <= Sep_DI(1,8)
            d = 8;
        elseif Svalues(i) <= Sep_DI(1,9)
            d = 9;
        elseif Svalues(i) <= Sep_DI(1,10)
            d = 10;
        end

        Sep_output = rmmissing([Sep_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Sep.Time(i))]);

    end

    Oct = Dataseries((month(Dataseries.Time)== 10),:);
    Oct_DI = prctile((Oct.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Ovalues = Oct.Variables;
    Oct_output = timetable();

    for i = 1:size(Oct)
        if Ovalues(i) <= Oct_DI(1,1)
            d = 1;
        elseif Ovalues(i) <= Oct_DI(1,2)
            d = 2;
        elseif Ovalues(i) <= Oct_DI(1,3)
            d = 3;
        elseif Ovalues(i) <= Oct_DI(1,4)
            d = 4;
        elseif Ovalues(i) <= Oct_DI(1,5)
            d = 5;
        elseif Ovalues(i) <= Oct_DI(1,6)
            d = 6;
        elseif Ovalues(i) <= Oct_DI(1,7)
            d = 7;
        elseif Ovalues(i) <= Oct_DI(1,8)
            d = 8;
        elseif Ovalues(i) <= Oct_DI(1,9)
            d = 9;
        elseif Ovalues(i) <= Oct_DI(1,10)
            d = 10;
        end

        Oct_output = rmmissing([Oct_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Oct.Time(i))]);

    end

    Nov = Dataseries((month(Dataseries.Time)== 11),:);
    Nov_DI = prctile((Nov.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Nvalues = Nov.Variables;
    Nov_output = timetable();

    for i = 1:size(Nov)
        if Nvalues(i) <= Nov_DI(1,1)
            d = 1;
        elseif Nvalues(i) <= Nov_DI(1,2)
            d = 2;
        elseif Nvalues(i) <= Nov_DI(1,3)
            d = 3;
        elseif Nvalues(i) <= Nov_DI(1,4)
```

```
            d = 4;
        elseif Nvalues(i) <= Nov_DI(1,5)
            d = 5;
        elseif Nvalues(i) <= Nov_DI(1,6)
            d = 6;
        elseif Nvalues(i) <= Nov_DI(1,7)
            d = 7;
        elseif Nvalues(i) <= Nov_DI(1,8)
            d = 8;
        elseif Nvalues(i) <= Nov_DI(1,9)
            d = 9;
        elseif Nvalues(i) <= Nov_DI(1,10)
            d = 10;
        end

        Nov_output = rmmissing([Nov_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Nov.Time(i))]);

    end

    Dec = Dataseries((month(Dataseries.Time)== 12),:);
    Dec_DI = prctile((Dec.MonthlyPrecipitationTotal_millimetres_),[10 20 30 40 50 60 70 80
 90 100]);
    Dvalues = Dec.Variables;
    Dec_output = timetable();

    for i = 1:size(Dec)
        if Dvalues(i) <= Dec_DI(1,1)
            d = 1;
        elseif Dvalues(i) <= Dec_DI(1,2)
            d = 2;
        elseif Dvalues(i) <= Dec_DI(1,3)
            d = 3;
        elseif Dvalues(i) <= Dec_DI(1,4)
            d = 4;
        elseif Dvalues(i) <= Dec_DI(1,5)
            d = 5;
        elseif Dvalues(i) <= Dec_DI(1,6)
            d = 6;
        elseif Dvalues(i) <= Dec_DI(1,7)
            d = 7;
        elseif Dvalues(i) <= Dec_DI(1,8)
            d = 8;
        elseif Dvalues(i) <= Dec_DI(1,9)
            d = 9;
        elseif Dvalues(i) <= Dec_DI(1,10)
            d = 10;
        end

        Dec_output = rmmissing([Dec_output; timetable(d, station, coordinates{1,1}, coordi
nates{1,2}, 'RowTimes', Dec.Time(i))]);

    end

    monthly_output = [monthly_output; Jan_output; Feb_output; Mar_output; Apr_output; May_
output; Jun_output; Jul_output; Aug_output; Sep_output; Oct_output; Nov_output; Dec_output
];
```

Extract 2007 Monthly Deciles

```
    ZeroSevenMonths = timetable2table(monthly_output(((year(monthly_output.Time)== 2007)),
:),'ConvertRowTimes',true);
```

Plot Decile Bands

```
    subplot(2,2,1);
    bar(Annual_DI.');
    xlabel('Annual Deciles');
    ylabel('Rainfall (mm)');

    subplot(2,2,2);
    bar(Quarterly_DI.');
    xlabel('Quarterly Deciles');
    ylabel('Rainfall (mm)');

    subplot(2,2,3);
    bar(Winter_DI.');
    xlabel('Winter Deciles');
    ylabel('Rainfall (mm)');

    subplot(2,2,4);
    bar(GrowingPeriod_DI.');
    xlabel('Growing Period Deciles');
    ylabel('Rainfall (mm)');

    sgtitle(station);

    fpath = 'C:\Users\Jessica\Desktop\Uni QLD\2020\Drought Thesis\Data\BOM Downloads\Figur
es\Decile Bands';
    saveas(gcf, fullfile(fpath, station),'jpeg');
```

Plot Raw Rainfall & Deciles

```
    subplot(2,2,1);
    plot(Annual_Rainfall.Time,Annual_Rainfall.MonthlyPrecipitationTotal_millimetres_,'Disp
layName','Rainfall');
    hold on;
    yline(Annual_DI(1,1),'-r','Serious Rainfall Deficiency','FontSize',8,'LabelVerticalAli
gnment','bottom','DisplayName','Decile 1');
    yline(Annual_DI(1,3),'-g','FontSize',8,'LabelVerticalAlignment','bottom','DisplayName'
,'Decile 3');
    yline(Annual_DI(1,5),'--k','Median','FontSize',8,'LabelVerticalAlignment','middle','Di
splayName','Decile 5');
    legend('Location','best','Orientation','horizontal','FontSize',8);
    xlabel('Year');
    ylabel('Annual Rainfall (mm)');

    subplot(2,2,2);
    plot(Quarterly_Rainfall.Time,Quarterly_Rainfall.MonthlyPrecipitationTotal_millimetres_
,'DisplayName','Rainfall');
    hold on;
    yline(Quarterly_DI(1,1),'-r','Serious Rainfall Deficiency','FontSize',8,'LabelVertical
Alignment','bottom','DisplayName','Decile 1');
    yline(Quarterly_DI(1,3),'-g','FontSize',8,'LabelVerticalAlignment','bottom','DisplayNa
me','Decile 3');
    yline(Quarterly_DI(1,5),'--k','Median','FontSize',8,'LabelVerticalAlignment','middle',
'DisplayName','Decile 5');
    legend('Location','best','Orientation','horizontal','FontSize',8);
```

```
    xlabel('Year');
    ylabel('Quarterly Rainfall (mm)');

    subplot(2,2,3);
    plot(Winter_Rainfall.Time,Winter_Rainfall.MonthlyPrecipitationTotal_millimetres_,'Disp
layName','Rainfall');
    hold on;
    yline(Winter_DI(1,1),'-r','Serious Rainfall Deficiency','FontSize',8,'LabelVerticalAli
gnment','bottom','DisplayName','Decile 1');
    yline(Winter_DI(1,3),'-g','FontSize',8,'LabelVerticalAlignment','bottom','DisplayName'
,'Decile 3');
    yline(Winter_DI(1,5),'--k','Median','FontSize',8,'LabelVerticalAlignment','middle','Di
splayName','Decile 5');
    legend('Location','best','Orientation','horizontal','FontSize',8);
    xlabel('Year');
    ylabel('Winter Rainfall (mm)');

    subplot(2,2,4);
    plot(GrowingPeriod_Rainfall.Time,GrowingPeriod_Rainfall.MonthlyPrecipitationTotal_mill
imetres_,'DisplayName','Rainfall');
    hold on;
    yline(GrowingPeriod_DI(1,1),'-r','Serious Rainfall Deficiency','FontSize',8,'LabelVert
icalAlignment','bottom','DisplayName','Decile 1');
    yline(GrowingPeriod_DI(1,3),'-g','FontSize',8,'LabelVerticalAlignment','bottom','Displ
ayName','Decile 3');
    yline(GrowingPeriod_DI(1,5),'--k','Median','FontSize',8,'LabelVerticalAlignment','midd
le','DisplayName','Decile 5');
    legend('Location','best','Orientation','horizontal','FontSize',8);
    xlabel('Year');
    ylabel('Growing Period Rainfall (mm)');

    sgtitle(station);

    fpath = 'C:\Users\Jessica\Desktop\Uni QLD\2020\Drought Thesis\Data\BOM Downloads\Figur
es\Deciles';
    saveas(gcf, fullfile(fpath, station),'jpeg');
    clf
```

```
end
```

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K-test

Conducts Kolmogorov-Smirnov testing (k-test) to determine the goodness-of-fit of the rainfall and temperature data to specified distributions

Contents

Load Data & Test Against Normal Distribution

```
x = table2array(rmmissing(WindmereData1)); % Assign x to Windmere Monthly Rainfall Records
pd = fitdist(x,'Normal');
[muHat,sigmaHat] = normfit(x)
kstest(x,pd)
```

Plot Results

```
figure(1)
cdfplot(x)
hold on
x_values = linspace(min(x),max(x));
plot(x_values,normcdf(x_values,muHat,sigmaHat),'r-')
legend('Empirical CDF','Normal CDF','Location','best')
[h,p,ks2stat]=kstest(x,pd)
```

Test Against Normal Distribution

```
pd = fitdist(x,'Gamma');
[phat,pci] = gamfit(x)
kstest(x,pd)
```

Plot Results

```
figure(2)
cdfplot(x)
hold on
x_values = linspace(min(x),max(x));
plot(x_values,gamcdf(x_values,phat(1),phat(2)),'r-')
legend('Empirical CDF','Gamma CDF','Location','best')
[h,p,ks2stat]=kstest(x,pd)
```

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MK Test

Reliabilty Test using MK Trend Test

Contents

Read File & Check for NaNs

```
clear all
datain_all = (readtable('Seasonal MK Minaru Months.csv'));
datain = table2array(datain_all);
for i = 1:size(datain,1)
    if isnan(datain(i,1))
        break;
    end
end
datain = datain(1:i,:);
```

Calculate MK Trend for Each Individual Month

```
datain = table2array(datain_all(:,[1, 2, 3]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Jan = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 4]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Feb = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 5]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Mar = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 6]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Apr = [Zs_out sig_out tausea_out Sens_out]

datain = table2array(datain_all(:,[1, 2, 7]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
May = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 8]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Jun = [Zs_out sig_out tausea_out Sens_out];
```

```
datain = table2array(datain_all(:,[1, 2, 9]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Jul = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 10]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Aug = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 11]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Sep = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 12]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Oct = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 13]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Nov = [Zs_out sig_out tausea_out Sens_out];

datain = table2array(datain_all(:,[1, 2, 14]));
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(datain, 0.05, 1, 1);
Dec = [Zs_out sig_out tausea_out Sens_out];
```

Run MK Test for Growing, Winter & Anual Periods

```
datain_all = (readtable('Seasonal MK Minaru Growing Period.csv'));
growingperiod = table2array(datain_all(:,[1, 2, 3]));
for i = 1:size(growingperiod,1)
    if isnan(growingperiod(i,1))
        break;
    end
end
growingperiod = growingperiod(1:i,:);
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(growingperiod, 0.05, 1, 1);
Growing_Period = [Zs_out sig_out tausea_out Sens_out];

datain_all = (readtable('Seasonal MK Minaru Winter.csv'));
winter = table2array(datain_all(:,[1, 2, 3]));
for i = 1:size(winter,1)
    if isnan(winter(i,1))
        break;
    end
end
winter = winter(1:i,:);
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(winter, 0.05, 1, 1);
Winter = [Zs_out sig_out tausea_out Sens_out];

datain_all = (readtable('Seasonal MK Minaru Annual.csv'));
annual = table2array(datain_all(:,[1, 2, 3]));
for i = 1:size(annual,1)
    if isnan(annual(i,1))
```

```
        break;
    end
end
annual = annual(1:i,:);
[taubsea_out, tausea_out, Sens_out, h_out, sig_out sigAdj_out Zs_out Zmod_out Ss_out Sigma
s_out CIlower_out CIupper_out] = sktt(annual, 0.05, 1, 1);
Annual = [Zs_out sig_out tausea_out Sens_out];
```

Post Processing

```
Output = [ Jan; Feb; Mar; Apr; May; Jun; Jul; Aug; Sep; Oct; Nov; Dec; Annual; Winter; Gro
wing_Period];
```

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Moving Average

Plots Carnamah, Minaru and Windmere stations 5 year moving average rainfall over the reliability test period

Contents

Read & Format data

```
AnnualCarnamah = readtable('Annual_Carnamah.csv','Format','%s %f');
AnnualMinaru = readtable('Annual_Minaru.csv','Format','%s %f');
AnnualWindmere = readtable('Annual_Windmere.csv','Format','%s %f');

    y = AnnualWindmere.Year;
    dmy = strcat(y);
    t = datetime(AnnualWindmere{:,1},'InputFormat','yyyy','Format','yyyy');

lag = 5;
m_Windmere = movmean(AnnualWindmere.Rainfall,lag);
m_Carnamah = movmean(AnnualCarnamah.Rainfall,lag);
m_Minaru = movmean(AnnualMinaru.Rainfall,lag);
```

Moving Average Plots

```
plot(t,AnnualWindmere{:,2},'b',t,m_Windmere,'c');
legend('Windmere Rainfall','Windmere 5 Year Average');
ylabel('Rainfall (mm)');
title('Rainfall & Moving Average');
hold on;

plot(t,AnnualCarnamah{:,2},'r',t,m_Carnamah,'m');
legend('Carnamah Rainfall','Carnamah 5 Year Average');
plot(t,AnnualMinaru{:,2},'g',t,m_Minaru,'y');
legend('Minaru Rainfall','Minaru 5 Year Average');
hold off;

plot(t,m_Windmere,'b', t,m_Minaru,'m', t,m_Carnamah,'g');
legend('Windmere 5 Year Average', 'Minaru 5 Year Average', 'Carnamah 5 Year Average');
ylabel('Rainfall (mm)');
xlabel('Year');
title('Rainfall Moving Average (1977-2014)');
```

Published with MATLAB® R2019b

Standardised Precipitation-Evapotranspiration Index (pathFindFAO56.m)

pathFindFAO56.m finds the station files in directory, preprocesses the data before running SPEI.m available in Matlab® Climate Data Toolbox. Plots and output files for use in ArcGIS® are then created.

Contents

Find Files in Directory

```
clc

fds = fileDatastore('C:\Users\Jessica\Desktop\Uni QLD\2020\Drought Thesis\Data\SILO Downlo
ads\FAO56\*.csv', 'ReadFcn', @importdata)

fullFileNames = fds.Files

numFiles = length(fullFileNames)

output = timetable();

% Loop over all files reading them in and plotting them.

for k = 1 : numFiles
```

```
    pathparts = strsplit(fullFileNames{k},filesep);
    station = string(pathparts(11));
    fprintf('Now reading file %s\n',station);

    if       contains(station,'Windmere')
                coordinates = table(-29.8514, 116.2863,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Windmere';
    elseif   contains(station,'Warradarge')
                coordinates = table(-30.0722, 115.3136,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Warradarge';
    elseif   contains(station,'Leeman')
                coordinates = table(-29.9486, 114.9781,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Leeman';
    elseif   contains(station,'Coorow')
                coordinates = table(-29.8814, 116.0229,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Coorow';
    elseif   contains(station,'Minaru')
                coordinates = table(-29.8497, 116.2289,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Minaru';
    elseif   contains(station,'Koobabie')
```

```
                coordinates = table(-29.9414, 116.2003,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Koobabie';
    elseif   contains(station,'Hakea')
                coordinates = table(-30.0989, 116.2339,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Hakea';
    elseif   contains(station,'Ytiniche')
                coordinates = table(-30.0706, 116.2092,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Ytiniche';
    elseif   contains(station,'Latham')
                coordinates = table(-29.7586, 116.4444,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Latham';
    elseif   contains(station,'Perenjori')
                coordinates = table(-29.4417, 116.2875,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Perenjori';
    elseif   contains(station,'Perangery')
                coordinates = table(-29.3692, 116.4061,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Perangery';
    elseif   contains(station,'Wanarra')
                coordinates = table(-29.5147, 116.8011,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Wanarra';
    elseif   contains(station,'Oaklands')
                coordinates = table(-29.4667, 116.1325,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Oaklands';
    elseif   contains(station,'Five Gums')
                coordinates = table(-29.4847, 116.0703,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Five Gums';
    elseif   contains(station,'Eneabba')
                coordinates = table(-29.8183, 115.2722,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Eneabba';
    elseif   contains(station,'Twin Hills')
                coordinates = table(-29.6708, 115.3636,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Twin Hills';
    elseif   contains(station,'Carnamah')
                coordinates = table(-29.6886, 115.8872,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Carnamah';
    elseif   contains(station,'Highfields')
                coordinates = table(-29.6006, 115.9392,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Highfields';
    elseif   contains(station,'Green Grove')
                coordinates = table(-29.5486, 115.0689,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Green Grove';
    elseif   contains(station,'Irwin House')
                coordinates = table(-29.2236, 115.1075,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Irwin House';
    elseif   contains(station,'Dongara')
                coordinates = table(-29.2528, 114.9306,'VariableNames',{'Latitude', 'Longi
```

```
tude'});
                station = 'Dongara';
    elseif   contains(station,'Mindarra')
                coordinates = table(-29.0636, 115.1753,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Mindarra';
    elseif   contains(station,'Three Springs')
                coordinates = table(-29.5339, 115.7628,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Three Springs';
    elseif   contains(station,'Fairfield')
                coordinates = table(-29.4714, 115.8528,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Fairfield';
    elseif   contains(station,'Mingenew')
                coordinates = table(-29.1906, 115.4414,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Mingenew';
    elseif   contains(station,'Yandanooka')
                coordinates = table(-29.2872, 115.6331,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Yandanooka';
    elseif   contains(station, 'Arena')
                coordinates = table(-29.3586, 115.4503,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Arena';
    elseif   contains(station,'Yarragadee')
                coordinates = table(-29.0767, 115.4092,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Yarragadee';
    elseif   contains(station,'Manarra')
                coordinates = table(-29.0711, 115.6261,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Manarra';
    elseif   contains(station,'South Holmwood')
                coordinates = table(-29.0364, 115.5536,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'South Holmwood';
    elseif   contains(station,'Strawberry North')
                coordinates = table(-29.1514, 115.2428,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Strawberry North';
    elseif   contains(station,'Morowa')
                coordinates = table(-29.2103, 116.0089,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Morowa';
    elseif   contains(station,'Canna')
                coordinates = table(-28.8975, 115.8627,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Canna';
    elseif   contains(station,'Pindawa')
                coordinates = table(-28.8956, 115.8106,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Pindawa';
    elseif   contains(station,'Mallee Vale')
                coordinates = table(-29.2419, 115.7794,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Mallee Vale';
    elseif   contains(station,'Nindethana Farm')
                coordinates = table(-28.8114, 115.9675,'VariableNames',{'Latitude', 'Longi
tude'});
```

```
                station = 'Nindethana Farm';
        elseif  contains(station,'Mellenbye')
                coordinates = table(-28.8883, 116.1947,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Mellenbye';
        elseif  contains(station,'Yongarloo')
                coordinates = table(-29.1858, 115.7406,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Yongarloo';
        elseif  contains(station,'Bowgada')
                coordinates = table(-29.3303, 116.1433,'VariableNames',{'Latitude', 'Longi
tude'});
                station = 'Bowgada';
        end
```

Read Data

```
    Tbl = readtable(fullFileNames{k}); %Import SILO data
    tempo = table2array(Tbl(:,2)); %Read time (dd/mm/yyyy)
    prec = table2array(Tbl(:,3)); %Read daily rainfall (mm)
    PET = table2array(Tbl(:,9)); %Read daily Morton's Potential Evapotranspiration (mm)
```

Adjust PET for Crop Coefficient (Kc) according to stage of season

```
    rawdata = timetable(prec,PET,'RowTimes',tempo);

    for i = 1:height(rawdata)
        if month(rawdata.Time) == 6
            rawdata.PET(i) = rawdata.PET(i)*0.725;
        elseif or(month(rawdata.Time) == 7, month(rawdata.Time) == 8)
            rawdata.PET(i) = rawdata.PET(i)*1.15;
        else
            rawdata.PET(i) = rawdata.PET(i)*0.3;
        end
    end

    pevap = rawdata.PET;
    t = rawdata.Time;
    rawdata_m = retime(rawdata,'monthly','sum');
```

Process and plot

```
    subplot(5,1,1);
    plot(rawdata_m.Time,rawdata_m.prec,'b',rawdata_m.Time,rawdata_m.PET,'r');
    hold on;
    title({station; 'Raw Monthly Data'});
    xlabel('Time'); ylabel('Millimeteres');

    subplot(5,1,2);
    [s,tint] = spei(t,prec,pevap,'integrationtime',1);
    SPEI_1 = timetable(s,'RowTimes',tint);
    plot(tint,s,'Color',[0.4940 0.1840 0.5560]);
    hold on;
    x = datetime(1975,01,1):datetime(2020,05,31);
    y1 = 2;
    y2 = -2;
    p = plot(x,y1*ones(size(x)),x,y2*ones(size(x)),'Color','r','LineStyle','--'); % plot e
```

```
tremely wet and dry limits
    y3 = 1;
    y4 = -1;
    q = plot(x,y3*ones(size(x)),x,y4*ones(size(x)),'Color',[1 0.5 0],'LineStyle','--');
    title('Scale = 1 month');
    xlabel('Time'); ylabel('SPEI');

    subplot(5,1,3);
    [s,tint] = spei(t,prec,pevap,'integrationtime',3);
    SPEI_3 = timetable(s,'RowTimes',tint);
    plot(tint,s,'Color',[0.4940 0.1840 0.5560]);
    hold on;
    y1 = 2;
    y2 = -2;
    p = plot(x,y1*ones(size(x)),x,y2*ones(size(x)),'Color','r','LineStyle','--');
    y3 = 1;
    y4 = -1;
    q = plot(x,y3*ones(size(x)),x,y4*ones(size(x)),'Color',[1 0.5 0],'LineStyle','--');
    title('Scale = 3 months');
    xlabel('Time'); ylabel('SPEI');

    subplot(5,1,4);
    [s,tint] = spei(t,prec,pevap,'integrationtime',6);
    SPEI_6 = timetable(s,'RowTimes',tint);
    plot(tint,s,'Color',[0.4940 0.1840 0.5560]);
    hold on;
    y1 = 2;
    y2 = -2;
    p = plot(x,y1*ones(size(x)),x,y2*ones(size(x)),'Color','r','LineStyle','--');
    y3 = 1;
    y4 = -1;
    q = plot(x,y3*ones(size(x)),x,y4*ones(size(x)),'Color',[1 0.5 0],'LineStyle','--');
    title('Scale = 6 months');
    xlabel('Time'); ylabel('SPEI');

    subplot(5,1,5);
    [s,tint] = spei(t,prec,pevap,'integrationtime',12);
    SPEI_12 = timetable(s,'RowTimes',tint);
    plot(tint,s,'Color',[0.4940 0.1840 0.5560]);
    hold on;
    y1 = 2;
    y2 = -2;
    p = plot(x,y1*ones(size(x)),x,y2*ones(size(x)),'Color','r','LineStyle','--');
    y3 = 1;
    y4 = -1;
    q = plot(x,y3*ones(size(x)),x,y4*ones(size(x)),'Color',[1 0.5 0],'LineStyle','--');
    title('Scale = 12 months');
    xlabel('Time'); ylabel('SPEI');

    fpath = 'C:\Users\Jessica\Desktop\Uni QLD\2020\Drought Thesis\Data\SILO Downloads\FAO5
6';
    saveas(gcf, fullfile(fpath, station));
    saveas(gcf, fullfile(fpath, station),'jpeg');
    clf

   point = synchronize(SPEI_1, SPEI_3, SPEI_6, SPEI_12); % retrieving output for ArcGIS ma
pping
   len = length(point.Time);
   point = [point repelem(coordinates,len,1)]; % adding coordinates
   output = vertcat(output, point);
```

```
    Jan = timetable2table(output(((month(output.Time)== 1) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Feb = timetable2table(output(((month(output.Time)== 2) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Mar = timetable2table(output(((month(output.Time)== 3) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Apr = timetable2table(output(((month(output.Time)== 4) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    May = timetable2table(output(((month(output.Time)== 5) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Jun = timetable2table(output(((month(output.Time)== 6) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Jul = timetable2table(output(((month(output.Time)== 7) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Aug = timetable2table(output(((month(output.Time)== 8) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Sep = timetable2table(output(((month(output.Time)== 9) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Oct = timetable2table(output(((month(output.Time)== 10) & (year(output.Time)== 2007)),
:),'ConvertRowTimes',false);
    Nov = timetable2table(output(((month(output.Time)== 11) & (year(output.Time)== 2007)),
:),'ConvertRowTimes',false);
    Dec = timetable2table(output(((month(output.Time)== 12) & (year(output.Time)== 2007)),
:),'ConvertRowTimes',false);
    Jun_zerosix = timetable2table(output(((month(output.Time)== 6) & (year(output.Time)==
2006)),:),'ConvertRowTimes',false);
```

```
end
```

Save Output to File

```
writetimetable(output,'SPEI.xlsx');
writetable(Jan,'SPEI_Jan2007.xlsx');
writetable(Feb,'SPEI_Feb2007.xlsx');
writetable(Mar,'SPEI_Mar2007.xlsx');
writetable(Apr,'SPEI_Apr2007.xlsx');
writetable(May,'SPEI_May2007.xlsx');
writetable(Jun,'SPEI_Jun2007.xlsx');
writetable(Jul,'SPEI_Jul2007.xlsx');
writetable(Aug,'SPEI_Aug2007.xlsx');
writetable(Sep,'SPEI_Sep2007.xlsx');
writetable(Oct,'SPEI_Oct2007.xlsx');
writetable(Nov,'SPEI_Nov2007.xlsx');
writetable(Dec,'SPEI_Dec2007.xlsx');
writetable(Jun_zerosix,'SPEI_Jun2006.xlsx');
```

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Standardised Precipitation Index (pathFind.m)

pathFind.m finds the station files in directory, preprocesses the data before running Taesam Lee's SPI.m. Plots and output files for use in ArcGIS® are then created.

Contents

Find Files in Directory

```
clc

fds = fileDatastore('C:\Users\Jessica\Desktop\Uni QLD\2020\Drought Thesis\Data\BOM Downloa
ds\*\*Data1.csv', 'ReadFcn', @importdata)

fullFileNames = fds.Files

numFiles = length(fullFileNames)

output = timetable();
```

Loop Over All Station Files

```
for k = 1 : numFiles
```

```
    pathparts = strsplit(fullFileNames{k},filesep);
    station = string(pathparts(10));
    fprintf('Now reading file %s\n',station);
```

Specify Station Coordinates

```
    if       station == 'Windmere'
                coordinates = table(-29.8514, 116.2863,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Warradarge'
                coordinates = table(-30.0722, 115.3136,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Leeman'
                coordinates = table(-29.9486, 114.9781,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Coorow'
                coordinates = table(-29.8814, 116.0229,'VariableNames',{'Latitude', 'Longi
tude'});
```

```
    elseif   station == 'Minaru'
                coordinates = table(-29.8497, 116.2289,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Koobabie'
                coordinates = table(-29.9414, 116.2003,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Hakea'
                coordinates = table(-30.0989, 116.2339,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Ytiniche'
                coordinates = table(-30.0706, 116.2092,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Latham'
                coordinates = table(-29.7586, 116.4444,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Perenjori'
                coordinates = table(-29.4417, 116.2875,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Perangery'
                coordinates = table(-29.3692, 116.4061,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Wanarra'
                coordinates = table(-29.5147, 116.8011,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Oaklands'
                coordinates = table(-29.4667, 116.1325,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Five Gums'
                coordinates = table(-29.4847, 116.0703,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Eneabba'
                coordinates = table(-29.8183, 115.2722,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Twin Hills'
                coordinates = table(-29.6708, 115.3636,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Carnamah'
                coordinates = table(-29.6886, 115.8872,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Highfields'
                coordinates = table(-29.6006, 115.9392,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Green Grove'
                coordinates = table(-29.5486, 115.0689,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Irwin House'
                coordinates = table(-29.2236, 115.1075,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Dongara'
                coordinates = table(-29.2528, 114.9306,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Mindarra'
                coordinates = table(-29.0636, 115.1753,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Three Springs'
                coordinates = table(-29.5339, 115.7628,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Fairfield'
                coordinates = table(-29.4714, 115.8528,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Mingenew'
```

```
            coordinates = table(-29.1906, 115.4414,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Yandanooka'
            coordinates = table(-29.2872, 115.6331,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Arena'
            coordinates = table(-29.3586, 115.4503,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Yarragadee'
            coordinates = table(-29.0767, 115.4092,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Manarra'
            coordinates = table(-29.0711, 115.6261,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'South Holmwood'
            coordinates = table(-29.0364, 115.5536,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Strawberry North'
            coordinates = table(-29.1514, 115.2428,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Morowa'
            coordinates = table(-29.2103, 116.0089,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Canna'
            coordinates = table(-28.8975, 115.8627,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Pindawa'
            coordinates = table(-28.8956, 115.8106,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Mallee Vale'
            coordinates = table(-29.2419, 115.7794,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Nindethana Farm'
            coordinates = table(-28.8114, 115.9675,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Mellenbye'
            coordinates = table(-28.8883, 116.1947,'VariableNames',{'Latitude', 'Longi
tude'});
    elseif   station == 'Yongarloo'
            coordinates = table(-29.1858, 115.7406,'VariableNames',{'Latitude', 'Longi
tude'});

    end
```

Format Data

```
    Tbl = readtable(fullFileNames{k},'Format','%s %s %s %s %f %s'); % Reads .csv downloade
d directly from Climate Data Online
    Rainfall = table2array(Tbl(:,5)); % Reads rainfall data from file
    y = Tbl.Year;
    m = Tbl.Month;
    m_y = strcat(m, {'-'}, y);
    t = datetime(m_y,'InputFormat','MM-yyyy','Format','MMM-yyyy'); % Format time eg. MAY-2
007
```

Process & Plot

```
    subplot(6,1,1); % Raw rainfall
```

```
    data = timetable(Rainfall,'VariableNames',{'Rainfall'},'Rowtimes',t);
    filteredData = retime(data,'regular','TimeStep',calmonths(1));
    plot(filteredData.Time,filteredData.Rainfall,'b');
    hold on;
    title({station; 'Raw Data'});
    xlabel('Time'); ylabel('Rainfall (mm)');

    subplot(5,1,2); % One month SPI
    f_data_1 = SPI(Rainfall,1,12);
    data_1 = timetable(f_data_1.','VariableNames',{'OneMonthSPI'},'Rowtimes',t);
    filteredData_1 = retime(data_1,'regular','TimeStep',calmonths(1));
    plot(filteredData_1.Time,filteredData_1.OneMonthSPI,'Color',[0.4940 0.1840 0.5560]);
    hold on;
    % Plot extreme wet and dry limits:
    y1 = 2;
    y2 = -2;
    p = plot(filteredData_1.Time,y1*ones(size(filteredData_1.Time)),filteredData_1.Time,y2
*ones(size(filteredData_1.Time)),'Color','r','LineStyle','--'); % plot etremely wet and dr
y limits
    y3 = 1;
    y4 = -1;
    q = plot(t,y3*ones(size(t)),t,y4*ones(size(t)),'Color',[1 0.5 0],'LineStyle','--');
    title('Scale = 1');
    xlabel('Time'); ylabel('1 monthly SPI');

    subplot(5,1,3); % Three month SPI
    f_data_3 = SPI(Rainfall,3,12);
    ts = length(t)-length(f_data_3)+1;
    data_3 = timetable(f_data_3.','VariableNames',{'ThreeMonthSPI'},'Rowtimes',t(ts:end));
    filteredData_3 = retime(data_3,'regular','TimeStep',calmonths(1));
    plot(filteredData_3.Time,filteredData_3.ThreeMonthSPI,'Color',[0.4940 0.1840 0.5560]);
    hold on;
    y1 = 2;
    y2 = -2;
    p = plot(filteredData_3.Time,y1*ones(size(filteredData_3.Time)),filteredData_3.Time,y2
*ones(size(filteredData_3.Time)),'Color','r','LineStyle','--'); % plot etremely wet and dr
y limits
    y3 = 1;
    y4 = -1;
    q = plot(t,y3*ones(size(t)),t,y4*ones(size(t)),'Color',[1 0.5 0],'LineStyle','--');
    title('Scale = 3');
    xlabel('Time'); ylabel('3 monthly SPI');

    subplot(5,1,4); % Six month SPI
    f_data_6 = SPI(Rainfall,6,12);
    ts = length(t)-length(f_data_6)+1;
    data_6 = timetable(f_data_6.','VariableNames',{'SixMonthSPI'},'Rowtimes',t(ts:end));
    filteredData_6 = retime(data_6,'regular','TimeStep',calmonths(1));
    plot(filteredData_6.Time,filteredData_6.SixMonthSPI,'Color',[0.4940 0.1840 0.5560]);
    hold on;
    y1 = 2;
    y2 = -2;
    p = plot(filteredData_6.Time,y1*ones(size(filteredData_6.Time)),filteredData_6.Time,y2
*ones(size(filteredData_6.Time)),'Color','r','LineStyle','--'); % plot etremely wet and dr
y limits
    y3 = 1;
    y4 = -1;
    q = plot(t,y3*ones(size(t)),t,y4*ones(size(t)),'Color',[1 0.5 0],'LineStyle','--');
    title('Scale = 6');
    xlabel('Time'); ylabel('6 monthly SPI');
```

```
    subplot(5,1,5); % Twelve month SPI
    f_data_12 = SPI(Rainfall,12,12);
    ts = length(t)-length(f_data_12)+1;
    data_12 = timetable(f_data_12.','VariableNames',{'TwelveMonthSPI'},'Rowtimes',t(ts:end
));
    filteredData_12 = retime(data_12,'regular','TimeStep',calmonths(1));
    plot(filteredData_12.Time,filteredData_12.TwelveMonthSPI,'Color',[0.4940 0.1840 0.5560
]);
    hold on;
    y1 = 2;
    y2 = -2;
    p = plot(t,y1*ones(size(t)),t,y2*ones(size(t)),'Color','r','LineStyle','--');
    y3 = 1;
    y4 = -1;
    q = plot(t,y3*ones(size(t)),t,y4*ones(size(t)),'Color',[1 0.5 0],'LineStyle','--');
    title('Scale = 12');
    xlabel('Time'); ylabel('12 monthly SPI');
```

Save Figures to File

```
    fpath = 'C:\Users\Jessica\Desktop\Uni QLD\2020\Drought Thesis\Data\BOM Downloads\Figur
es\SPI';
    saveas(gcf, fullfile(fpath, station));
    clf
```

Compile Output

```
    point = synchronize(filteredData_1, filteredData_3, filteredData_6, filteredData_12);
% retrieving output for ArcGIS mapping
    len = length(point.Time);
    point = [point repelem(coordinates,len,1)]; % adding coordinates
    output = vertcat(output, point);

    Jan = timetable2table(output(((month(output.Time)== 1) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Feb = timetable2table(output(((month(output.Time)== 2) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Mar = timetable2table(output(((month(output.Time)== 3) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Apr = timetable2table(output(((month(output.Time)== 4) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    May = timetable2table(output(((month(output.Time)== 5) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Jun = timetable2table(output(((month(output.Time)== 6) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Jul = timetable2table(output(((month(output.Time)== 7) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Aug = timetable2table(output(((month(output.Time)== 8) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Sep = timetable2table(output(((month(output.Time)== 9) & (year(output.Time)== 2007)),:
),'ConvertRowTimes',false);
    Oct = timetable2table(output(((month(output.Time)== 10) & (year(output.Time)== 2007)),
:),'ConvertRowTimes',false);
    Nov = timetable2table(output(((month(output.Time)== 11) & (year(output.Time)== 2007)),
:),'ConvertRowTimes',false);
    Dec = timetable2table(output(((month(output.Time)== 12) & (year(output.Time)== 2007)),
:),'ConvertRowTimes',false);
```

```
end
```

Save Output to File

```
writetimetable(output,'SPI.xlsx');
writetable(Jan,'SPI_Jan2007.xlsx');
writetable(Feb,'SPI_Feb2007.xlsx');
writetable(Mar,'SPI_Mar2007.xlsx');
writetable(Apr,'SPI_Apr2007.xlsx');
writetable(May,'SPI_May2007.xlsx');
writetable(Jun,'SPI_Jun2007.xlsx');
writetable(Jul,'SPI_Jul2007.xlsx');
writetable(Aug,'SPI_Aug2007.xlsx');
writetable(Sep,'SPI_Sep2007.xlsx');
writetable(Oct,'SPI_Oct2007.xlsx');
writetable(Nov,'SPI_Nov2007.xlsx');
writetable(Dec,'SPI_Dec2007.xlsx');
```

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Stats

Calculates statistics for MK reliability test

Contents

Read Monthly Data

```
clear all
datain_all = (readtable('Seasonal MK Windmere.csv'));
mnth = table2array(datain_all(:,[1, 2, 5]));
for i = 1:size(mnth,1)   %---Check for NaNs---%
    if isnan(mnth(i,1))
        break;
    end
end
mnth = mnth(1:i,:);
```

Calculate Annual Statistics

```
annual = reshape(mnth(:,3),12,38);
annual_sum = sum(annual);
M_annual = mean(annual_sum);
Med_annual = median(annual_sum);
Mx_annual = max(annual_sum);
Mn_annual = min(annual_sum);
St_dev_annual = std(annual_sum);
Coef_Var_annual = St_dev_annual/M_annual*100;
```

Calculate Statistics for Individual Months

```
Jan_Rainfall = [];
Feb_Rainfall = [];
Mar_Rainfall = [];
Apr_Rainfall = [];
May_Rainfall = [];
Jun_Rainfall = [];
Jul_Rainfall = [];
Aug_Rainfall = [];
Sep_Rainfall = [];
Oct_Rainfall = [];
Nov_Rainfall = [];
Dec_Rainfall = [];

for j = 1:size(mnth,1)
    if mnth(j,2) == 1
```

```
        Jan_Rainfall = [Jan_Rainfall, mnth(j,3)];
        M_Jan = mean(Jan_Rainfall);
        Med_Jan = median(Jan_Rainfall);
        Mx_Jan = max(Jan_Rainfall);
        Mn_Jan = min(Jan_Rainfall);
        St_dev_Jan = std(Jan_Rainfall);
        Coef_Var_Jan = St_dev_Jan/M_Jan*100;
    end
    if mnth(j,2) == 2
        Feb_Rainfall = [Feb_Rainfall, mnth(j,3)];
        M_Feb = mean(Feb_Rainfall);
        Med_Feb = median(Feb_Rainfall);
        Mx_Feb = max(Feb_Rainfall);
        Mn_Feb = min(Feb_Rainfall);
        St_dev_Feb = std(Feb_Rainfall);
        Coef_Var_Feb = St_dev_Feb/M_Feb*100;
    end
    if mnth(j,2) == 3
        Mar_Rainfall = [Mar_Rainfall, mnth(j,3)];
        M_Mar = mean(Mar_Rainfall);
        Med_Mar = median(Mar_Rainfall);
        Mx_Mar = max(Mar_Rainfall);
        Mn_Mar = min(Mar_Rainfall);
        St_dev_Mar = std(Mar_Rainfall);
        Coef_Var_Mar = St_dev_Mar/M_Mar*100;
     end
     if mnth(j,2) == 4
        Apr_Rainfall = [Apr_Rainfall, mnth(j,3)];
        M_Apr = mean(Apr_Rainfall);
        Med_Apr = median(Apr_Rainfall);
        Mx_Apr = max(Apr_Rainfall);
        Mn_Apr = min(Apr_Rainfall);
        St_dev_Apr = std(Apr_Rainfall);
        Coef_Var_Apr = St_dev_Apr/M_Apr*100;
     end
     if mnth(j,2) == 5
        May_Rainfall = [May_Rainfall, mnth(j,3)];
        M_May = mean(May_Rainfall);
        Med_May = median(May_Rainfall);
        Mx_May = max(May_Rainfall);
        Mn_May = min(May_Rainfall);
        St_dev_May = std(May_Rainfall);
        Coef_Var_May = St_dev_May/M_May*100;
     end
     if mnth(j,2) == 6
        Jun_Rainfall = [Jun_Rainfall, mnth(j,3)];
        M_Jun = mean(Jun_Rainfall);
        Med_Jun = median(Jun_Rainfall);
        Mx_Jun = max(Jun_Rainfall);
        Mn_Jun = min(Jun_Rainfall);
        St_dev_Jun = std(Jun_Rainfall);
        Coef_Var_Jun = St_dev_Jun/M_Jun*100;
     end
     if mnth(j,2) == 7
        Jul_Rainfall = [Jul_Rainfall, mnth(j,3)];
        M_Jul = mean(Jul_Rainfall);
        Med_Jul = median(Jul_Rainfall);
        Mx_Jul = max(Jul_Rainfall);
        Mn_Jul = min(Jul_Rainfall);
        St_dev_Jul = std(Jul_Rainfall);
        Coef_Var_Jul = St_dev_Jul/M_Jul*100;
```

```
      end
      if mnth(j,2) == 8
         Aug_Rainfall = [Aug_Rainfall, mnth(j,3)];
         M_Aug = mean(Aug_Rainfall);
         Med_Aug = median(Aug_Rainfall);
         Mx_Aug = max(Aug_Rainfall);
         Mn_Aug = min(Aug_Rainfall);
         St_dev_Aug = std(Aug_Rainfall);
         Coef_Var_Aug = St_dev_Aug/M_Aug*100;
      end
      if mnth(j,2) == 9
         Sep_Rainfall = [Sep_Rainfall, mnth(j,3)];
         M_Sep = mean(Sep_Rainfall);
         Med_Sep = median(Sep_Rainfall);
         Mx_Sep = max(Sep_Rainfall);
         Mn_Sep = min(Sep_Rainfall);
         St_dev_Sep = std(Sep_Rainfall);
         Coef_Var_Sep = St_dev_Sep/M_Sep*100;
      end
      if mnth(j,2) == 10
         Oct_Rainfall = [Oct_Rainfall, mnth(j,3)];
         M_Oct = mean(Oct_Rainfall);
         Med_Oct = median(Oct_Rainfall);
         Mx_Oct = max(Oct_Rainfall);
         Mn_Oct = min(Oct_Rainfall);
         St_dev_Oct = std(Oct_Rainfall);
         Coef_Var_Oct = St_dev_Oct/M_Oct*100;
      end
      if mnth(j,2) == 11
         Nov_Rainfall = [Nov_Rainfall, mnth(j,3)];
         M_Nov = mean(Nov_Rainfall);
         Med_Nov = median(Nov_Rainfall);
         Mx_Nov = max(Nov_Rainfall);
         Mn_Nov = min(Nov_Rainfall);
         St_dev_Nov = std(Nov_Rainfall);
         Coef_Var_Nov = St_dev_Nov/M_Nov*100;
      end
      if mnth(j,2) == 12
         Dec_Rainfall = [Dec_Rainfall, mnth(j,3)];
         M_Dec = mean(Dec_Rainfall);
         Med_Dec = median(Dec_Rainfall);
         Mx_Dec = max(Dec_Rainfall);
         Mn_Dec = min(Dec_Rainfall);
         St_dev_Dec = std(Dec_Rainfall);
         Coef_Var_Dec = St_dev_Dec/M_Dec*100;
      end
end
```

Calculate Winter Statistics

```
season = table2array(datain_all(:,[1, 3, 5, 4]));
for k = 1:size(season,1)
    if isnan(season(k,1))
       break;
    end
end
season = season(1:k,:);

Season_sum = [];
Winter_Rainfall = [];
```

```
for l = 1:size(season,1)

    if season(l,2) == 3
       Winter_Rainfall = [Season_sum; season(l,1) season(l,3)];
       [u,~,idx] = unique(Winter_Rainfall(:,1));
       Season_sum = [u, accumarray(idx, (Winter_Rainfall(:,2)))];
       Winter_Rainfall = Season_sum(:,2);

       M_Winter = mean(Winter_Rainfall);
       Med_Winter = median(Winter_Rainfall);
       Mx_Winter = max(Winter_Rainfall);
       Mn_Winter = min(Winter_Rainfall);
       St_dev_Winter = std(Winter_Rainfall);
       Coef_Var_Winter = St_dev_Winter/M_Winter*100;
    end
end
```

Calculate Growing Period Statistics

```
Period_sum = [];
GrowingPeriod_Rainfall = [];

for l = 1:size(season,1)
    if season(l,4) == 1
       GrowingPeriod_Rainfall = [Period_sum; season(l,1) season(l,3)];
       [u,~,idx] = unique(GrowingPeriod_Rainfall(:,1));
       Period_sum = [u, accumarray(idx, (GrowingPeriod_Rainfall(:,2)))];
       GrowingPeriod_Rainfall = Period_sum(:,2);

       M_GrowingPeriod = mean(GrowingPeriod_Rainfall);
       Med_GrowingPeriod = median(GrowingPeriod_Rainfall);
       Mx_GrowingPeriod = max(GrowingPeriod_Rainfall);
       Mn_GrowingPeriod = min(GrowingPeriod_Rainfall);
       St_dev_GrowingPeriod = std(GrowingPeriod_Rainfall);
       Coef_Var_GrowingPeriod = St_dev_GrowingPeriod/M_GrowingPeriod*100;
    end
end
```

Post Processing

```
Jan = {'Jan' M_Jan Med_Jan Mx_Jan Mn_Jan St_dev_Jan Coef_Var_Jan};
Feb = {'Feb' M_Feb Med_Feb Mx_Feb Mn_Feb St_dev_Feb Coef_Var_Feb};
Mar = {'Mar' M_Mar Med_Mar Mx_Mar Mn_May St_dev_Mar Coef_Var_Mar};
Apr = {'Apr' M_Apr Med_Apr Mx_Apr Mn_Apr St_dev_Apr Coef_Var_Apr};
May = {'May' M_May Med_May Mx_May Mn_May St_dev_May Coef_Var_May};
Jun = {'Jun' M_Jun Med_Jun Mx_Jun Mn_Jun St_dev_Jun Coef_Var_Jun};
Jul = {'Jul' M_Jul Med_Jul Mx_Jul Mn_Jul St_dev_Jul Coef_Var_Jul};
Aug = {'Aug' M_Aug Med_Aug Mx_Aug Mn_Aug St_dev_Aug Coef_Var_Aug};
Sep = {'Sep' M_Sep Med_Sep Mx_Sep Mn_Sep St_dev_Sep Coef_Var_Sep};
Oct = {'Oct' M_Oct Med_Oct Mx_Oct Mn_Oct St_dev_Oct Coef_Var_Oct};
Nov = {'Nov' M_Nov Med_Nov Mx_Jan Mn_Jan St_dev_Jan Coef_Var_Jan};
Dec = {'Dec' M_Dec Med_Dec Mx_Dec Mn_Dec St_dev_Dec Coef_Var_Dec};
Annual = {'Annual' M_annual Med_annual Mx_annual Mn_annual St_dev_annual Coef_Var_annual};
Winter = {'Winter' M_Winter Med_Winter Mx_Winter Mn_Winter St_dev_Winter Coef_Var_Winter};
Growing_Period = {'Growing Period' M_GrowingPeriod Med_GrowingPeriod Mx_GrowingPeriod Mn_G
rowingPeriod St_dev_GrowingPeriod Coef_Var_GrowingPeriod};
```

```
Values = [Jan; Feb; Mar; Apr; May; Jun; Jul; Aug; Sep; Oct; Nov; Dec; Annual; Winter; Grow
ing_Period];
Output = cell2table(Values,'VariableNames',{'Time Series' 'Mean (mm)' 'Median (mm)' 'Max (
mm)' 'Min (mm)' 'St Dev.' 'Coef. Var'});
```

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Regression_SPI.m

Reads 3-month SPI output to generate Linear Regression Analysis (Used in a similar fashion for Monthly Deciles

Contents

Read SPI Output

```
output = rmmissing(output);
locate = contains(output.Station, 'Windmere');
W_output = output(locate,2);

S = timerange('1977-01-01','2019-12-31');
W_output = W_output(S,:);
```

Calclulate Drought Duration

```
startTime = W_output(W_output.ThreeMonthSPI <= -1,:);
endTime = W_output(W_output.ThreeMonthSPI >= 0,:);
range = synchronize(startTime,endTime);
binaryArray = [~isnan(range.ThreeMonthSPI_startTime)];
measurements = regionprops(logical(binaryArray), 'Area');
allLengths = [measurements.Area]';
append = [];
for i = 1:length(allLengths)
    append = [append repelem(allLengths(i),allLengths(i))];
end
droughtlength = [startTime table(append')];

toDelete = [];
for i = 1:size(droughtlength)
toDelete = [toDelete droughtlength.Var1(i)> 1 && droughtlength.Var1(i) == droughtlength.Va
r1(i+1)];
end
toDelete = logical([0 toDelete(:,1:end-1)]');
droughtlength(toDelete,:) = [];
```

Plot

```
all = W_output(timerange('1980-01-01','2020-12-31'),:);
x1 = datenum(droughtlength.Time);
y1 = droughtlength.Var1;

[p1,S1] = polyfit(x1,y1,1);
[y_fit1,delta1] = polyval(p1,x1,S1);
polyfitn(x1,y1,1)

x2 = datenum(W_output.Time);
y2 = W_output.ThreeMonthSPI;
```

```
[p2,S2] = polyfit(x2,y2,1);
[y_fit2,delta2] = polyval(p2,x2,S2);
polyfitn(x2,y2,1)
```

Plot Data & Fit

```
figure(1)
hold on
bar(datenum(droughtlength.Time),droughtlength.Var1,'FaceColor',[0 0 1],'EdgeColor',[0 0 1]
)
plot(x1,y_fit1,'-r')
dateFormat = 10;
datetick('x',dateFormat)
hold off
title('Linear Fit of 3-Month SPI Drought Duration for Windmere')
legend('Data','Linear Fit')
xlabel('Years')
ylabel('Months')
ylim = get(gca,'ylim');
xlim = get(gca,'xlim');
text(xlim(1)+1000,ylim(2)-1.5,(['y = ',num2str(p1(1)),'*x + ','(',num2str(p1(2)),')']));

figure(2)
hold on
plot(x2,y2,'b')
polyval(p2, 737943); % Calculate estimated value for 01-Jun-2020
plot(x2,y_fit2,'-r')
plot(x2,y_fit2+2*delta2,'m--',x2,y_fit2-2*delta2,'m--')
dateFormat = 10;
datetick('x',dateFormat)
hold off
title('Linear Fit of 3-Month SPI for Windmere with 95% Prediction Interval')
legend('Data','Linear Fit','95% Prediction Interval')
xlabel('Years')
ylabel('Months')
ylim = get(gca,'ylim');
xlim = get(gca,'xlim');
text(xlim(1)+1000,ylim(2)-1.5,(['y = ',num2str(p2(1)),'*x + ','(',num2str(p2(2)),')']));
```

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